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THE MEASURABLE ME - THE INFLUENCE OF SELF-TRACKING ON THE USER EXPERIENCE

PhD Series 37-2015

Mimmi Sjöklint

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The PhD School of LIMAC

PhD Series 37.2015

CBS



COPENHAGEN BUSINESS SCHOOL
HANDELSHØJSKOLEN

The Measurable Me

The Influence of Self-tracking on the User Experience

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To curiosity

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Abstract

The proliferation of technological enhancements has fundamentally changed the relationship between the individual and technology. One particular change is the increased dispersion of technology in everyday experiences through personalized information technology (IT), such as smartphones, laptops, tablets and wearable technology. This development has brought about the rise of experiential computing, which refers to the “mediation of embodied experiences in every day activities through everyday artifacts that have embedded computing capabilities” (Yoo, 2010, p.213; Jain, 2003). The emphasis is thus placed on the relationship that occurs between the user and technology as the lived experience is mediated to the user through data dashboard. This potentially transformative relationship is both intimate and complex and spurs the research interest, which asks how the user is influenced by the exposure to personal data captured by experiential computing devices and how it alters the perception of personal performance.

One type of activity stemming from the dispersion of experiential computing is self-tracking. Self-tracking is a way for the user to capture and measure intimate details of the self, by using IT to collect, index and analyze personal data on life experiences. For example, the user might use an activity tracker, like the Jawbone UP, to gather numerical data on daily step and sleep activity. The exposure to this data may transform or distort the way the user initially perceived the activity by getting a new visual expression of what has occurred.

To better understand the user’s reaction and counter-reactions to using experiential tools, this research suggests placing the focus on the user and analyzing it through a behavioral economics perspective. This is done by conducting empirical studies with a mixed method approach. The first study is a field study that investigates the influence on performance and perception by wearing a self-tracking device. The second study is an in-depth interview study that studies experienced self-trackers by exploring further into the perceptions of the user.

This dissertation contributes to a deeper understanding of how the self-tracking user is affected by the use of experiential computing devices and the subsequent exposure to personal data. The findings suggest that the user’s analysis steps and sleep performance goes through a complex reflective process after the exposure to data that influences the perception of the initial experience. When this process involves unsatisfactory data, the user will reject the data and adopts coping tactics. The coping tactics are dismissal, procrastination, selective attention and intentional neglect.

Sammanfattning

Utvecklingen av teknologiska verktyg har förändrat samspelet mellan individen och teknologin. En särskilt påtaglig förändring är den ökade spridningen av teknologi i vardagliga situationer, genom bruk av personliga IT verktyg, såsom smartphones, bärbara datorer, plattor samt s.k. wearables eller wearable technology, teknologi som bärs på kroppen i form av armband, glasögon och andra format. Utvecklingen uppmuntrar en ökad relation mellan användare och teknologi i vardagliga begivenheter. Fenomenet kallas för 'experiential computing', nämligen teknologi som fångar upplevelsen som sker mellan just individen och teknologin för att sedan omvandla detta till ett digitalt format som sedan speglas åter till användaren (Jain, 2003; Yoo, 2010). Denna avhandling utforskar detta transformativa förhållande och frågar hur användarens uppfattning om personlig prestation påverkas av att bli exponerad av personlig data.

'Experiential computing' har gett upphov till nya aktiviteter som själv-spårning, även kallat egen-mätning och 'self-tracking'. Själv-spårning är en aktivitet där en användare samlar numerisk data om sig själv genom att använda datoriserade verktyg. Det är ett sätt att indexera och analysera personliga aspekter om livshändelser, precis som att skriva en dagbok eller att göra ett fotoalbum. Det innebär att en användare, exempelvis, använder aktivitetsmätare, som Jawbone UP, för att samla numerisk data kring hur mycket man går och sover dagligen.

Denna avhandling fokuserar på användarens upplevelse och den invecklade mänskliga relationen till teknologin. För att undersöka reaktioner samt motreaktioner så tillämpas ett teoretiskt perspektiv från behavioral economics (Kahneman 2003; även kallad beteendekonometri). Två empiriska studier utforskar hur högteknologiska aktivitetsmätare används, vilket består av en kvantitativ fältstudie med nya användare och en djupgående kvalitativ intervjustudie med erfarna användare. Genom att utgå från användaren är det vidare möjligt att bättre förstå det individuella perspektivet under exponering av personlig data.

Denna avhandling bidrar till ökad kunskap kring användningen av teknologi, såsom 'experiential computing', i vardagliga situationer för att samla digital data om upplevelser. Studierna ger en fördjupad förståelse för vad som händer vid exponering av sådan personlig data. Resultaten visar att användarens analys av personliga data går genom en komplicerad reflektions- och existentiell process som mynnar ut i olika reaktioner, såsom försvarsmekanismer. Fyra försvarsmekanismer identifierades: avfärda, fördröja, selektiv uppmärksamhet och försummelse.

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1. INTRODUCTION

This dissertation investigates how the user's perceptions of experiences is influenced by using experiential computing while engaging in the activity of self-tracking for self-quantification. This is done by conducting an exploratory mixed method study of the self-tracking user, consisting of a field study and an interview study. The chapter starts by introducing the research interest, followed by the research questions. Thereafter, an account of the research context is presented. Then the scope and limitations are underlined, followed by key definitions and the dissertation outline.

1.1 Research interest

The proliferation of technological enhancements has fundamentally changed the interaction between information technology (IT) and the individual. New activities and experiences are continuously generated and transferred into everyday space through the use of personalized IT devices, including laptops, tablets, smartphones and wearable technology (Jain, 2003; Yoo, 2010). Given their constant presence now in our everyday existence (e.g., described by Bell & Gemmell, 2007; Doherty et al., 2012; Sellen, Whittaker, & Sellen, 2010), these enhanced tools allow the subtleties of life to be captured, monitored and digitalized (Newell & Marabelli, 2015).

The increasing convergence between individuals and IT gives rise to the concept of experiential computing that involves "digitally mediated embodied experiences in everyday activities through everyday artifacts that have embedded computing capabilities" (Yoo, 2010, p.213). The concept places emphasis on the experience between technology and the user, rather than the user's experience of the technology itself. According to this understanding, the user is not interpreting nor experiencing the technology, but is embodied through the capture of the technology (Yoo, 2010). The technology and the information that it produces should not be considered a representation nor an alter ego of the user (Ihde, 1990), but part of an embodied relationship. The development indicates that the contemporary IT user has expanded his or her informational needs as compared to when situated within an organization (Lin, Huang, & Hsu, 2015). This suggest a

shift from the traditional utility and task-performance focus (Lamb & Kling, 2003). Instead, a greater experiential focus is in the spotlight, where users are presented with alternative ways of accessing, interacting and utilizing different types of data about themselves. The emergence of experiential computing encourages the notion that the user does not consider technology as separate, but instead as an integrated part of everyday activities through everyday artifacts. The technology is thus a lens that mediates between the user and the world and it is one that sometimes shapes and even transforms the lived experience (Yoo, 2010).

One type of activity that has emerged through experiential computing is called self-tracking. This dissertation investigates the emerging trend of self-tracking with a specific focus on the purpose of self-quantification for self-reflection. Self-tracking essentially means that the individual is collecting data about him- or herself with the assistance of experiential computing devices (also known as experiential devices). For example, a user might want to know more about daily activity, such as step and movement activity and choose to utilize an app, such as Apple Healthkit or Google Fit. Both apps are integrated parts in the iOS or Android smartphone systems and run in the background, tracking how many steps the user takes during the day. The user is then able to monitor the personal data on a daily basis.

Other common self-tracking activities include managing personal finances through mobile apps like Mint, monitoring sleeping patterns with SleepCycle or logging running routes with RunKeeper. The tools capture user experiences and translates it into personal digitalized data that can be seen on a screen of the experiential device. The self-tracking activity is thus a way of digitalizing and quantifying activities and experiences of personal performance, whether it involves steps, sleep, mood or personal finances. The activity of self-tracking for self-quantification emphasizes the role of data as an influence on evaluating, reflecting and understanding the self (Li et al., 2010; Sjöklint, Constantiou, & Trier, 2013; Swan, 2012). It is argued that these activities lead to increased self-reflection, and even self-knowledge (Huldtgren, Wiggers, & Jonker, 2014). Some studies also posit that the increase of such self-awareness inspires changes in both attitude and behavior (DiClemente, Marinilli, Singh, & Bellino, 2001; Fritz, Huang, Murphy, & Zimmermann, 2014). This research projects dives right into this development

and seeks to explore the role that self-tracking for self-quantification plays in relation to the individual's perception of lived experiences.

The catalyst that formed my interest in this topic was twofold: the emerging use of data for personal measurement in an online context and my personal experiences with self-tracking. The two currents spurred an interest in exploring how the translation of everyday activities and experiences into digital and numerical data affects the user's perception of those same experiences. Personal application and a careful literature review cemented my interest in the pursuit of understanding how experiential computing influences self-tracking activities, which in turn influences the user's perception about the self and related experiences.

Furthermore, the user's perspective is interesting to develop within IS research, as it has received less attention than a system perspective in the past. For example, "IS researchers have paid little attention to the evaluation of technologies with an interpretive framework that focuses on user experience" (Pallud & Monod, 2010, p.564). Supporters of this approach argue that the transformative nature of IT presents an opportunity to "expand the intellectual boundaries of the IS research community beyond the traditional focus of organizational computing" (Yoo, 2010, p.220). This is supported by other academics who agree that such a fundamental shift in technology should be further incorporated into IS research, instead of becoming isolated within current organizational and industry confines. Instead, new research challenges exist for approaching the dispersion of IT in individual everyday activities. For example, Oinas-Kukkonen, Lyytinen, & Yoo (2010) state that research should extend to both individual and organizational levels, and not merely the organizational level where the structural aspects are highlighted instead of individual attributes. In this context, the authors ask how social networks change the attitude, beliefs and behavior of the user based on new types of knowledge harvested from such networks. This is also supported by Steiny & Kukkonen (2007). Moreover, Tilson, Lyytinen, & Sørensen (2010) propose that research must address the digital infrastructure, making it possible to better understand "individuals engaging in patterns of use across multiple devices and services while adapting to dynamically changing service ecologies..." (p.757). These examples indicate that the approach to the research interest of the user's perceptions through the assistance of experiential computing is both identified and of interest to the IS field.

There are other research disciplines that have identified the emergence of experiential computing and related activities, but the debate surrounding the growth of self-tracking activities remains open-ended and scattered. The terms used to discuss the topic are also varied. Predominantly, the focus is on the system's capabilities, as discussed by Doherty, Moulin, and Smeaton (2011) and Mann (1997). It has also been analyzed by exploring design possibilities, as done by Consolvo, McDonald, and Landay (2009). Some have also focused on how the system can be altered and upgraded to cater to the user (Li et al., 2010), whereas others criticize this approach and argue that it is too system-centric (Rooksby & Rost, 2014). Alternatively, there is an increasing interest of the possibilities for self-tracking in the health and medical fields (e.g., case studies by Paton, Hansen, Fernandez-Luque, & Lau, 2012) as well as the educational sector (Alrushiedat & Olfman, 2013; V. R. Lee, 2013). There has also been plenty of media buzz from popular outlets that often speculate around the pending success of wearables and whether they will have a positive effect on user's behavior (e.g., Economist, 2015; Quart, 2013).

This research aspires to contribute to the experiential computing's theoretical discussion by providing an empirical study that can support, extend and contrast the current assumptions. This should hold particular interest for the IS field, where this topic remains marginally researched despite the growing proliferation of experiential computing in the everyday activities of contemporary IT users. This dissertation thus focuses on the user and how perceptions of experienced events are influenced by experiential computing-related activities, such as self-tracking for self-quantification. A stronger understanding of the user's perspective might be useful to the underlying design goals and ambitions of the designed IT systems by improving knowledge of how each one is manipulated and understood by users. In the same way, it is also of interest to other academic fields, such as human computer interaction (HCI) and computer science, both of which attempt to design and create prototypes that are useful but which also help to influence a targeted behavior of the user. The research is also of relevance to the industry by showing the potential for further incorporating the user's perspective when addressing the development and marketing of self-tracking devices.

1.2 Research question

This study aims to contribute understanding about how an individual's perception is affected by engaging in self-tracking for self-quantification and subsequently being exposed to personal data. The main research question is:

- How does self-tracking through experiential computing influence the user's perceptions about personal performance?

In addition, two sub-questions are formulated to address and compare the two studies included in this research project.

- **Study 1:** How do new users experience and perceive the activity of self-tracking in terms of personal performance?
- **Study2:** How do experienced users experience and perceive the activity of self-tracking in terms of personal performance?

1.3 Exploring the research context

My first personal experience with self-tracking was with Moodscope, a mood-tracking application. At the time, I was vaguely acquainted with the movement called the Quantified Self, which is a group of continuously growing enthusiasts that engage in self-tracking as they pursue "self-knowledge through numbers" (Wolf, 2010). My curiosity grew regarding the possible motivation of numbers and I decided to try out mood-tracking. It was a regular, but slightly late November evening, around 22.00, in what had been a fairly overcast day. As the application dictates, I proceeded to answer the 20 mandatory questions about my emotional status followed by pressing the submit button, which will give the user a score between 1-100 on a graph. Right before I pressed the submit button, I took a moment to reflect on my personal status to see if I could guess my pending score. I contemplated that since it was a regular day in my regular routine, my result should be around average so maybe 50-60%.

I hit the submit button. I achieved 20%. I was horrified! My immediate reaction was: What is wrong with me? This was the first question, as opposed to: What is wrong with the system? Within the click of a button, I had abandoned my intuition and any reflective processes that occurred previously. I believed in the number and I believed the number was representative of me. Naturally, I was intrigued. Instead

of evaluating how and why the discrepancy between my number and the system's number had appeared, I had single-handedly decided to accept the system number as an absolute truth. This experience profoundly affected me and I realized the many opportunities and challenges that reside in exploring the research arena of self-tracking. This experience became the departure point for the investigation of self-tracking for the purpose of self-quantification.

My experiences of self-tracking are aligned with others that pursue self-knowledge through numbers. There is an organized movement of enthusiasts that conduct a wide variety of self-experiments for different reasons called the Quantified Self. The group has developed in an organized manner since 2007 when the meetup group "The Quantified Self" was established by Kevin Kelly and Gary Wolf in San Francisco (Wolf, 2010). The meetups were organized to share firsthand experiences using self-tracking methods and tools. Anyone was welcome to join in to hear stories as well as to share personal stories. The presentations are based on three questions: What did you do? How did you do it? What did you learn? (Quantified Self Questions, 2015). The members seek to monitor and measure aspects of life for self-quantification with the firm belief that it leads to enlightenment (Wolf, 2010). Such Quantified Self experiments are primarily of a personal nature and depart from the $n=1$ principle. The $n=1$ principle focuses on individual learning rather than seeking collective and generalizable results that can be applied to a mass population. This means that the Quantified Self members use themselves, and primarily themselves, as subjects, because the aim is a deeper self-knowledge rather than attempting to gain or distribute collective knowledge (M. Sjöklint et al., 2013). In essence, these measurement enthusiasts engage in these activities as a way of obtaining self-knowledge by gathering and aggregating various streams of data (e.g., Li et al., 2010).

Among the Quantified Self enthusiasts who have done different self-tracking experiments are Cousins (2010), Barooah (2011) and Schwartz (2014). Cousins (2010) engaged in self-tracking as a way of managing his battle with bipolar disorder for almost thirty years. Cousins was inspired to the degree that he decided to create his own mood-tracking tool based on an established psychological model. This tool developed into Moodscope, as mentioned earlier, a social site where the user can track his or her mood status and share the data with friends. In Cousins' case, he shared data with his friends so that they would get an indication

of how high or low his mood was on the given day. Another enthusiast, Barooah (2011), engaged in self-tracking to learn what food made him feel energized or lethargic. In order to do so he used a binary self-tracking system that assisted in prompting awareness around his eating habits so that he could make more mindful choices. In the end, this self-tracking process led him to shed over 20kgs. Schwartz (2014) decided to quantify his dating life, both past and present. In order to gain insights into his past, he gathered his data around his dating history, such as messaging history. After analyzing this, he found that messages between 200-300 characters were most successful in receiving replies from his respective love interest.

These examples showcase the variations of how the self-tracking user might pursue self-quantification to gain insight on personal performance and possibly even adopt behavioral changes. The self-tracking user goes through lived experiences with the help of experiential computing of different kinds, and as a result these experiences are investigated with the aim of learning more about the self. However, these examples should be considered as particularly in-depth and dedicated self-studies and might not represent how the general population of users of experiential devices might approach personal data. There are several academic studies surrounding those that identify with the Quantified Self movement and the complexities of designing the related systems (I. Li, Dey, & Forlizzi, 2011).

In order to gain more knowledge about self-tracking activities and the user behind them, the research topic could benefit from placing the focus on the user's perspective and how the interaction with personal data influences the user's perception of the self and the experience previously lived. Indeed, this is especially relevant now that self-tracking is becoming more dispersed and thus gaining traction in the public eye.

1.4 Research scope and limitations

The possibilities in studying self-tracking for the purpose of self-quantification are vast due to its emerging status within a general public and a growing interest by the research community (e.g. Bentley, Tollmar, & Stephenson, 2013; Rooksby & Rost, 2014; Yoo, 2010). In order to comprehensively contribute to a growing

research discussion, it is vital to present the scope of this project to better define its contribution.

The research scope is in the context of experiential computing with a focus on where self-tracking occurs, namely the everyday experience in which the user and the technology interact (Yoo, 2010). In order to understand and discuss this context, some of the vital components that inform self-tracking are presented below. The following section underlines where the emphasis of this research project is placed. The focus is on self-tracking for self-quantification to capture personal data of user experiences by adoption of IT artifacts.

Figure 1 illustrates a simplification of the steps that the self-tracking user engages in (while the forthcoming chapter on related literature presents a more nuanced and complex picture of the same development).

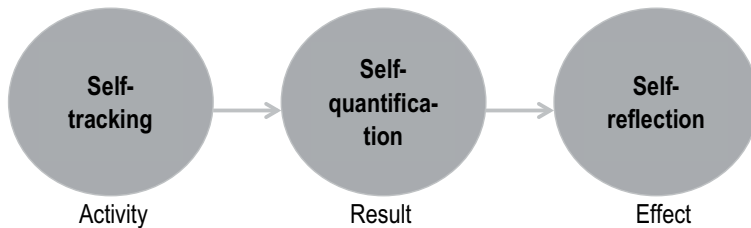


Figure 1. Simplified self-tracking process.

The terms self-tracking and self-quantification are essential concepts in the discussion. As mentioned earlier, self-tracking is understood an activity that uses technology for the purpose of capturing, indexing and analyzing personal data on aspects of everyday life, such as mental and physical performance (e.g., exercise, sleep), individual state (e.g., mood, blood sugar levels) and consumption (e.g., food, air quality) (Gemmell, Bell, & Lueder, 2006; I. Li et al., 2010; M. Sjöklint et al., 2013; Swan, 2012). Self-tracking is an umbrella term under which different types of tracking are placed and can thus be divided into more specific sub-categories, such as activity tracking, mood-tracking, bio-hacking and lifelogging (Doherty et al., 2011; Sellen et al., 2010). Self-tracking has as its aim the capture

and collection of personal data, which may be either qualitative or quantitative. In this research project, the outcome of interest is self-quantification.

Self-quantification is the output of the data collection of the personal and often intangible aspects of the self. The output is often visualized through an interface as numbers or a graph. Popular self-tracking activities related to physical performance will, for example, quantify the numbers of steps a person has taken per day.

This research project is particularly interested in self-tracking that occurs through the adoption of IT systems and devices that enable experiential computing, such as smartphone applications and wearable technology that are specifically purposed for this. (The research acknowledges but does not address manual logging that is done by hand, such as journaling or diary writing.) IT devices that are also linked to self-tracking activities are sometimes grouped under the name of personal informatics, namely a “class of systems that help people collect personally relevant information to improve self-knowledge” (Li et al., 2010, p.23). The availability and varieties of tools to facilitate self-tracking activity are continuously growing, particularly within the health, fitness and lifestyle arena (Bentley et al., 2013; Kamal, Fels, & Ho, 2010).

Technology that can be worn by the individual to measure various aspects is often referred to as wearable technology, because it is worn on the body to collect data about the user’s behavior (Lukowicz, Timm-Giel, Lawo, & Herzog, 2007). The devices should have automatic or semi-automatic systems to collect the data. This means that the personal data should primarily be collected in the background, rather than being recorded manually by the user. For example, an automatic system is Moves, a mobile app that automatically registers and showcases the user’s daily physical patterns, such as walking, commuting with local transport, biking and driving. Moreover, two particularly popular activity trackers, Jawbone UP and Fitbit, are devices that can be worn on the body and that automatically and ubiquitously track personal data, like steps, activities and sleep. Beyond this, there are multi-purpose devices that offer tracking as an addition to other functions, such as communication tools and GPS, like the Apple Watch, Moto 360 and Samsung Gear. These are not designed to be purely self-tracking devices but

should rather be characterized as smart-devices. In other words, this research project focuses on the use of self-tracking devices designed for this purpose.

Sometimes the automatic system is complemented with manual logging, where the user can enter data by hand, such as journaling or diary writing. This might be adding a meal or workout details that the system could not capture. Nevertheless, manual self-tracking is thus acknowledged as occasionally present in self-tracking system, but is not the focus of this dissertation (e.g. Pirzadeh, He, & Stolterman, 2013).

The focus is on personal data captured through the active use of self-tracking devices, rather than other types of personal data that are generated in an online setting, such as social networks. On a general level, personal data may refer to the numbers that are displayed in different types of visualizations in any online setting, such as websites or apps, and that are attributed to an individual. For example, personal data can be anything from sleep statistics in SleepCycle to Fitbit steps, and Moodscope scores, but it can also be Facebook likes, Twitter followers, Snapchat points, Researchgate scores or seller ratings on Ebay. The former are data on active self-tracking measurements while the latter are data on passive self-tracking measurements. Both types are considered to be personal data because they are attributed to a person and acquired through participation in the platforms. In essence, personal data can be any measurement that represents an aggregation of something that is attributed to an individual, including an activity, a state of mind, or an experience. The many variations of ratings, likes, followers and scores are all just different numbers with different terminology that are displayed in an online context.

Since this research project pursues an investigation of personal numbers that are collected by purposely adopted self-tracking tools, the social networking data might be present due to the context of contemporary users, but it is not viewed as relevant. This distinction is important because the Quantified Self movement has grown to incorporate qualitative self-trackers, often referred to as lifeloggers. For example, lifelogging might be self-tracking by wearing a camera to take photos every 30 seconds of your day or writing a diary about daily mood fluctuations. Although the lifelogging data collection could be turned into quantitative measures, i.e., by numbering the photos in categories, it is initially in a qualitative

form (Sellen et al., 2007). Self-tracking for the purpose of quantification is customarily gathered and retrieved in a numerical form by using the mobile applications and wearable technology already described (Consolvo et al., 2008; J. J. Lin, Mamykina, Lindtner, Delajoux, & Strub, 2006).

Last but not least, this research project is interested in the individual's perspective and the experiences related to the interaction with the personal data collected through experiential computing. Therefore, this study does not attempt to present design principles nor to design a system prototype to test, which is already well-documented within the HCI community (e.g., Consolvo et al., 2008; Lin, Mamykina, Lindtner, Delajoux, & Strub, 2006).

1.5 Empirical focus: Activity trackers as experiential computing devices

The experiential devices of interest in the forthcoming empirical study are self-trackers with the specific functionality of being activity trackers. The specific self-tracking devices of interest are Fitbit Flex and Jawbone UP. These devices are worn on the body and thus are referred to as wearable technology or wearables. They are designed to be worn all hours of the day, except during activities that could harm the device, such as swimming. When worn, each device measures the individual's activity in terms of steps and sleep. Thereafter the data is uploaded to accompanying software, often in the shape of a mobile app or desktop dashboard. The detail level of the data varies depending on the device. In Jawbone UP and Fitbit, both devices measure steps as in daily steps, and overall active time respective to idle time. When it comes to sleep, each device measures deep sleep, light sleep, how long it took to fall asleep, as well as any interruptions (i.e., waking up) in the night. It is also possible for the user to add manual data, such as food consumed, perception of mood and workouts.

The first study, a primarily quantitative field study, measures and observes the performance of entirely new Jawbone UP users and how the performance as well as perceptions develop over the first few weeks.

The second study, a qualitative in-depth interview study, further explores the perceptions of engaging in activity tracking and therefore gathers semi-structured interviews with experienced users of Fitbit Flex and Jawbone UP. The interviews

address the experiences of long-term users by sharing motivation, narratives, reactions and reflections on data over time.

The two devices involved in the studies—Jawbone UP and Fitbit Flex—are shown in the figure below. A more thorough account of these devices and their functionalities is presented in section 4.3.3.



Figure 2. Self-tracking devices: Jawbone UP and Fitbit Flex.

1.6 Key terms and definitions

This section provides an overview of the key definitions that are commonly referenced throughout the research project. For the sake of clarity, it is important to establish which terms are used to describe the phenomenon due to the emergent status of the research topic. This is because sometimes the same concept is discussed yet under the guise of a different term. The definitions are placed in alphabetical order.

Personal data refers to the quantified data, or numbers, that are collected by engaging in self-tracking activities for the purpose of self-quantification.

Quantified Self (QS) is a global community where the members engage in self-tracking in the pursuit of “self-knowledge through numbers” (Wolf, 2010). There are local meetups, online forums and two yearly conferences where they share and tell their stories.

Self-quantification is the activity of collecting personal data to perform self-evaluation through test, comparison and experimentation of personal data sets gathered through experiential computing devices, such as self-tracking devices, i.e., smart phones or wearable technology (Sjöklint, 2014). Self-quantified data is thus the user's personal experiences that are translated into a numerical format.

Self-tracking is the activity of using technology for the purpose of capturing, indexing and analyzing personal data on aspects of everyday life, such as mental and physical performance (e.g., exercise, sleep), individual state (e.g., mood, blood sugar levels) and consumption (e.g., food, air quality). The term self-tracking has sub-streams, such as "activity tracking," "bio-hacking" and "lifelogging." This research project looks specifically on activity tracking, although self-tracking is the main term used throughout the dissertation.

Self-tracking tools are the technological devices used by individuals to enable self-tracking. This tool is a specific type of experiential computing device, although not all experiential computing devices are self-tracking tools. The two types of self-tracking tools investigated in this research are Jawbone UP and Fitbit.

1.7 Chapter outline

Chapter 1 presents an introduction to the research arena of self-tracking for the purpose of self-quantification. After this, the initial research interest, questions and scope are presented. The context of the research interest is then further enhanced with elaboration and definitions.

Chapter 2 presents the theoretical background, namely experiential computing's emergence into self-tracking-related literature. This aims to give an overview of the emerging and assorted progression that the research topic has experienced. The focus is on experiential computing that enables self-tracking activities.

Chapter 3 presents a complementary yet independent section to the previous theoretical background that presents an additional theoretical lens for analysis, namely behavioral economics. The foundational pillars of behavioral economics are presented alongside relevant theoretical concepts, including heuristics and cognitive bias, which are used to discuss the results.

Chapter 4 presents the research methodology and the empirical investigation. The investigation rationale is presented and supported. The process and catalyzing outcome of the pilot study is followed by introduction to the two studies that were made in the course of this research project.

Chapter 5 presents the method and results of study 1. The first study is a field study that includes both quantitative and qualitative elements. It studies the new self-tracking user in relation to personal step and sleep performance and how it is developed during the few weeks of adoption.

Chapter 6 presents the method and results of study 2. The second study is an in-depth interview study and explores the experienced self-tracking users experiences and perceptions. It has a preliminary study using focus groups followed by an in-depth interview study. Each study has its own sub-chapter where method, results and discussion are given.

Chapter 7 presents the discussion and the main reflections of key contributions, results and findings. The chapter rounds up by discussing the limitations and implications of exploring possibilities for future research.

Chapter 8 is the concluding chapter where the discussion strands are gathered and summarized into a meaningful matrix of results.

1.8 Chapter summary

This chapter provides an introduction to the research interest, which is to investigate the emerging field of experiential computing, with a focus on self-tracking for the purpose of self-quantification. The introduction is followed by the main research question and sub-questions related to the forthcoming two studies. Thereafter, the research context is presented, followed by the scope and limitations of the project. In order to further explicate the research context, the empirical focus is placed on self-tracking with the help of activity trackers, such as Jawbone UP and Fitbit. Then key terms and definitions are outlined, followed by the chapter overview.

2. THEORETICAL BACKGROUND

2.1 Introduction to the theoretical background

This chapter starts with presenting the context of experiential computing. Next, self-tracking is presented as a type of activity that is facilitated by experiential computing. The aggregation for a personal archive is then elaborated upon, followed by the perspectives on what occurs after exposure and engagement with personal data. The role of data engagement is next presented in relation to proposed categories that endorse it; the challenges related to data engagement are identified. Finally, a summarizing commentary presents perspectives learnt and the methodology for investigating the research interest.

The research interest in this dissertation is to increase the understanding and theoretical conceptualization of the perception of the experience of self-tracking for self-quantification, which is an activity framed through experiential computing that enables the activity itself. Experiential computing is thus a relevant theoretical perspective to conceptualize self-tracking and serves as the foundation of how to address the research question. A deeper understanding of the self-tracking is also imperative to further the investigation in the direction proposed. For example, self-tracking is addressed in several research disciplines, such as design science, HCI (e.g., Li, Medynskiy, Froehlich, & Larsen, 2012), and health-related disciplines such as medicine and sports (Swan, 2009; Wiederhold, 2012). These are thus integrated to provide further insight into identifying possibilities and challenges in further research.

Figure 3 showcases the overall components that frame the research interest in this theoretical background chapter. It also serves as an overview of the structure of this chapter. The chapter starts with introducing the information technology context, namely experiential computing. With the help of this type of computing, everyday activities and experiences are captured. One of these activities is self-tracking, which is understood as the capturing and indexing of personal data, which then accumulates into a personal data archive as the product. The exposure of a personal data archive leads to participation of data through engagement. The

data engagement aims to lead to the outcome—self-reflection—and sometimes also into behavioral change.

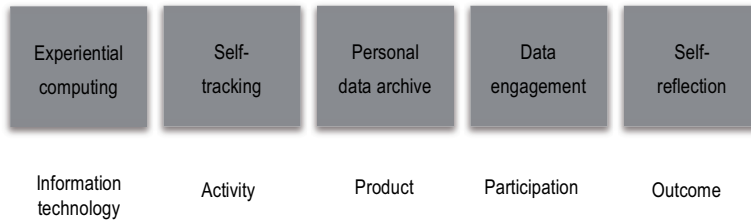


Figure 3. Structure of the components of the theoretical background.

The field of experiential computing “involves digitally mediated embodied experiences in everyday activities through everyday artifacts that have embedded computing capabilities” (Yoo, 2010, p.213). In this dissertation, the everyday artifacts are IT devices, which are the tools that initiate the process of self-tracking that allows a personal archive to accumulate. The product of self-tracking results in various measures of the self, which are understood as a type of digital personal archive. The personal archive in a digital form has mainly been researched through computer and software design that focuses on designing and studying prototypes. For example, Bell and Gemmell (2007) discussed the possibilities of adjusting and implementing technology that recorded life as heard, seen and sensed. The project was called My Life Bits and aimed at creating a lifelong archive of the individual’s experiences. Their work continued over several years and resulted in several texts, such as an article on a “personal database for everything” (Gemmell, Bell, & Lueder, 2006). The focus was primarily on the technological capabilities, but it also went beyond traditional computing that revolved around numbers and text. Instead, the wish was to create a digitalized archive that “records virtually everything in a person’s life” (Bell & Gemmell 2007, p. 95) by incorporating more human and experiential data elements, such as rich media (e.g., video, photos). Moreover, Czerwinski et al. (2006) further elaborated on the notion of recording life by addressing the challenges of using a personal archive, a seemingly desirable method of storage. These examples are representative of the discussion that evolved regarding the technological possibilities and challenges of creating a

personal archive. However, during this time, there was little emphasis on the discussion of the activity preceding the outcome, which is described next.

After the collection of a personal archive through self-tracking, the user is exposed to the content, the personal data. For example, the exposure might occur after the user wakes up from a night sleep and checks the data in the mobile app. It might also be that the user has walked to the supermarket and back, followed by checking the data. It is suggested that this exposure leads to user engagement that is, participating and sometimes interacting with the data presented to the user. The act of engagement itself is thus described as multifaceted and it is then subsequently discussed in a design-oriented context. The design perspective aims at addressing how technology can be altered and adjusted to address this multifaceted engagement (including the effects with or without a mobile interface). Many times, the aim is to design a system for optimal use for the user. For example, Consolvo, McDonald, and Landay (2009) propose a set of theory-driven design strategies to support behavior change. In this list of principles, they emphasize that the data collected should be controllable so that it “permit[s] the user to add to, edit, delete, and otherwise manipulate data” (p.409). This involves the user in reviewing the data and causing engagement by extension. Another example is Lin, Mamykina, Lindtner, Delajoux, and Strub (2006), who argue that a concrete challenge of a daily step goal leads to awareness of personal performance as well as the motivation to engage in both the self-tracking tool and the activity levels. After this, the chapter attempts to develop an understanding for the engagement processes by presenting the key self-tracking processes. Next, suggestions on how to design in ways that support user engagement are addressed. These examples are representative of how the discussion shifted focus from technological capabilities to design-oriented considerations related to interaction and interface. This acknowledged the activity of self-tracking, yet did not further divulge how it evolved. Since then, data engagement has been investigated by others (e.g., Karapanos, 2013; Li, Dey, & Forlizzi, 2010), yet the primary focus returns to the core need to create and design technology for the user, rather than the experience that lies between the technology and the user. The next step in further understanding how experiential computing has an impact on the user is to place the emphasis on the complexities of individual user experiences in self-tracking activity.

The literature collected for the purposes of this chapter derived from a number of controlled database queries. The main keywords were “experiential computing”, “self-tracking” and “quantified self”. These terms have various levels of abstraction, an approach which was useful to gain an overall understanding of the conceptual aspects of the research interest, and how those were related to activities of self-tracking and the Quantified Self movement. A more detailed account of the search for literature can be viewed in appendix A.

2.2 Context of experiential computing

The proliferation of technology has undergone great transformation from computer rooms to the personal desktop computer to the handheld smartphone that is used every day. Researchers argue that IT is now omnipresent in everyday life through the personal digital devices already mentioned: laptops, tablets, wearables and smartphones (Jain 2003; Yoo 2010; Ihde 1990). These devices neither look nor operate like traditional computing processors that had a fixed position on an office desk. The new types of IT artifacts are not merely functional and symbolic, but are increasingly personal as well as unobtrusive in their nature, factors which allow them to become a habitual part of the user’s life (Weiser, 1991; Yoo, 2010). This type of technology surrounds and accompanies us, our activities and endeavors in our daily lives in the form of a personal digital database (Bell & Gemmell, 2007; Doherty, Moulin, & Smeaton, 2011; Sellen et al., 2007).

It is suggested that these new types of IT artifacts are also increasingly socially embedded and the embedded capabilities enable new behaviors (Tilson et al., 2010). The extended presence but also capabilities of the technology make it possible to collect data on these new everyday experiences.

The technology surrounding us in everyday life has a transformative impact on our lived experiences (Jain, 2003; Yoo, 2010). It is the aim of this dissertation to contribute to the discussion of experiential computing by providing an empirical study that supports, extends and compares the current research on the topic. Currently, the impact of increasingly personal and everyday IT is relatively unnoticed in IS literature (Yoo, 2010; Yoo et al., 2010). The increased use of such technology is argued to be strongly related to “the rise of the digital native, along with the growth of ubiquitous information systems” and “potentially represents a

fundamental shift in our ‘paradigm’ for IS research” (Vodanovich et al., 2010, p.711). By embracing this development, the interest and intention is to consider the influence of IT as it applies beyond the workplace and to look at the everyday experiences in which users are continuously and constantly interacting with IT. This is because the “expansion of the influence of digital technology provides a critical opportunity to expand the intellectual boundaries of the IS research community beyond the traditional focus of organizational computing” (Yoo, 2010, p.220). There are opportunities in researching the different perspectives in an increasingly ubiquitous computing context, as proposed by Henfridsson & Lindgren (2005). They stress that the multi-contextuality of devices must be considered as ubiquitous computing is increasingly more common in everyday use. Ubiquitous computing might be a type of experiential computing that enables self-tracking, such as the mobile app Moves, but ubiquitous computing does not necessarily have self-tracking capabilities. Thus, it should be acknowledged, but at the same time referred to as a different yet related research direction that focuses on making technology available yet invisible to use. Experiential computing may thus make use of ubiquitous computing, but is focused on the experience capture, rather the shape and form of the technology.

Experiential computing can contribute to the IS field by “establishing a new domain of research on computing in everyday life experiences” (Yoo, 2010, p.213). It shifts focus from a system-centric view and towards the user where the information is central for the user, as has also been done in research around IT adoption by individuals (Venkatesh and Brown, 2001). However, the user’s information needs are complex as they are reflected in human needs and values. Experiential computing thus asserts that the user uses technology beyond the traditional task performance done in an organization, and extends it into private and social spheres where the IT artifact continuously changes in use and meaning (Yoo, 2010). The user changes and alters the IT artifact’s functionality and value by input from the device itself but also from the external surroundings.

This complexity makes it tempting to invite alternative perspectives that shed light on the individual needs, preferences and behavior that are shaped by underlying forces in the environment in which the individual is placed (e.g., Kahneman, 2003). The environment is the natural world or empirical world, where the individual resides and experiences life. Experiential computing focuses on the

embodiment relationship that occurs between technology, everyday experiences in the world, and people (Ihde, 1990; Yoo, 2010). It is the application of technology to assimilate and understand the overwhelming amount of information available by, for example, providing a computer-aided environment that supports the user's experiences (Jain, 2003). More specifically, experiential computing "involves digitally mediated embodied experiences in everyday activities through everyday artifacts that have embedded computing capabilities" (Yoo, p.213). The individual is thus considered a "walking data generator" (McAfee & Brynjolfsson, 2012, p.63) as he or she provides the context for the input, yet the data generated is unstructured and overwhelming until it is organized by an IT system (ibid). The experience of technology is not at the center, but rather the relationship is between the user and the lived world because "Technology is not being interpreted, nor is it being experienced as an end in itself. Instead, it directly shapes and occasionally transforms our lived experiences" (Yoo, 2010, p.218). In other words, the experience lies not within the technology, but within what is being experienced by the user in the world while simultaneously using and relating to the technology. Therefore, experiential computing is a type of mediator between the technology and the user of what is directly lived and experienced in the environment in which the individual exists. The technology is used to sense, capture and index the user's experiences, and therefore is a part of the experience rather than at the center of what is being experienced. At the same time, the technology is not believed to create representations of the experience, but it actually embodies the experienced as lived by the user.

Yoo (2010) presents four dimensions to demonstrate a conceptualization of the human experience as an interaction between the body and the environment, emphasizing that the experience lies between the technology and the user. The four dimensions are time, space, artifact and actor. The dimensions do not have priority over the other, but together they make a context in which the experience takes place. Experiential computing rests on partial or full mediation of the dimensions. This conceptualization is applied to understand how the experience emerges, as this is central to the continued investigation. This understanding also emphasizes that self-tracking tools are indeed experiential devices, rather than representational devices (Bødker, Gimpel, & Hedman, 2014; Yoo, 2010). The four dimensions are described in the figure and text below, as informed by Yoo (2010), and with an application of the context of self-tracking activity.

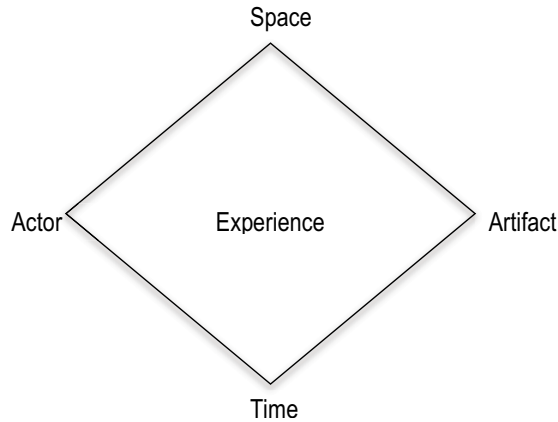


Figure 4. Schematic framework of experiential computing.

Space is an inherent part of the lived experience and a “structure that enables things to be connected as humans experience them” (Yoo 2010, p.219). The individual, who is an anchor in the lived experience, carries out an action that constructs the space. For example, the user is tracking a run through the park. As the user moves through the park, the space changes around the user because the user is moving. The data collected changes along with this action, as compared to if the user was standing still. While running, the user also experiences the space, more or less consciously. The digitalization of space occurs through the collection of data through the self-tracking device and encompasses the movement through space, in this example. The individual can therefore only be in one place, in the physical space, and not reside in several places at the same time (ibid). In a self-tracking context, the user can only reside in one space and the data is then collected in this space. Therefore, the space is inherently necessary to enable the experience of self-tracking to occur. The self-tracking activity itself does not necessarily shape the space, but only the actions of the individual.

Time is now, yet “temporary and in the process of becoming” or “temporally emergent” (Yoo, 2010, p.219). Much like space, time is also experienced through the human body. An experience is therefore temporary yet continuous, and occurs

at the cross of what has been and what is coming. The embodiment of the relationship between technology and user is thus intentional yet with dynamic elements (ibid). In the example of self-tracking, time is then a process, which suggests that it is relevant to discuss the stages that the user goes through during the time of an experience as these might vary and develop over time. The self-tracking activity captures what occurs in a space during a certain time, such as a run through the park. The spatiotemporal experience is important to the self-tracking activity, as it shapes the possibilities of the digitally mediated experience.

The actor is the individual participating in the experience, but also the surrounding actors residing in the natural world. The actor thus experiences other actors. The digitalization of actors occurs in several ways, e.g., through social networking sites (SNS) such as Facebook, Instagram and Snapchat. The relationships may be formal or informal in the natural world, but through digitalization they are not simply representations of a relationship, but are actually “relationships of a different kind” (ibid, p.220). In the self-tracking context, the actor may be the self-tracking user. The actor may also be in contact with others through social functions in the self-tracking, or by posting the personal data on SNS or other forums, such as blogs.

The artifact is referred to as an experiential device, and is something that exists in the real world and can be digitalized. The artifact may be the self-tracking device itself. It can also be the artifacts that reside in the natural world that the self-tracking device can capture and influence the experience, such as buildings, bricks, and cars, yet this dissertation focuses on the user and device relationship. By using artifacts with computing power, such as sensors or cameras, the artifacts of the real world can be transformed into digitized information. Moreover, the digitalized artifacts “can ‘interact’ and be associated with other digitalized artifacts” much like Web 2.0 services (Yoo 2010, p.219). For example, the self-tracking device may track the actor, but also the temperature and time in the space that the actor is residing.

An overview of the conceptualization and self-tracking contextualization is presented in the table below.

Dimension	Experiential computing	Self-tracking context
Space	Space is the "structure that enables things to be connected as humans experience them" (Yoo 2010, p.219).	The structure that enables self-tracking to take place, such as the individual partaking through performance in an event in the natural world, such as the physical location that surrounds, constitutes and affects performance of user.
Time	Time is "temporary and in the process of becoming" or "temporally emergent" (Yoo, 2010, p.219).	The self-tracking experience occurs in time and through time, and may change over time, hence unfolding a process.
Artifact	The artifact is the experiential device itself or something that exists in the natural world and can be digitalized through, e.g., sensors.	The artifact is the self-tracking device, or the items that are captured by this device.
Actors	The actor is the human, or the actors that the human is surrounded by. The digitalization of actors occur through, e.g., social networks such as Facebook.	The actor is the self-tracking user, yet may interact with others. This may occur in the natural world or in a digital format. The others may be or may not be self-tracking users.

Table 1. Four dimensions of experiential computing compared to self-tracking activity

The experiential device produces and organizes experiential data, or personal data, which is gathered from the user's embodied experiences. As the size of the sensors decrease and processing capabilities increase, these devices are also becoming more accessible and affordable to the general public who are increasingly taking interest (Dobbins, Merabti, Fergus, & Llewellyn-Jones, 2014). Academics observe that one type of experiential device is becoming increasingly popular, namely wearables (Mann, 1997; McCann & Bryson, 2009). The wearable device is technology that can be placed on the body with the aim of weaving technology and everyday life (Mann, 1997; Manyika, Chui, & Bughin, 2013; Martin, 2014). Wearables are particularly suitable for the purposes of experiential computing as they can be worn directly by an individual to collect data about everyday experiences (ibid). While the devices are usually for individual use, some are also designed to be shared amongst a group of people. In terms of individual use, Jawbone Up and Fitbit are devices to be worn everyday by the same individual and if done so, the device gathers data on embodied experiences such as physical

performance and sleep patterns. Another device is Nest, a home thermostat that learns and adapts to the users' habits and home turf. Nest thus learns the users' schedule, programs itself and can be controlled from a smartphone. The Nest is dependent on the space and the users occupying the space, while the Jawbone UP is influenced by a single user. These are both experiential devices that require different types of input. This study is focused on devices for individual use.

The use of experiential devices have been studied in the context of self-tracking as an activity of collecting personal data with the aim of gaining self-knowledge and changing behavior (I. Li et al., 2010; Wolf, 2010). The activity accumulates personal data that becomes a digital as well as personal archive of experiences, much the way a photo album is a visual archive of select experiences (Petrelli & Whittaker, 2010). Self-tracking is thus an activity that allows researchers to explore and understand the essence of experiential computing because it invites the technology to capture the user's activity and then it re-exposes the user to this activity in a new digital format. The user is thus interpreting personal experiences in an alternative form through the aid of technology. The technology is not the experience itself. The focus is on the interaction that embodies the experience where the user and the technology are deeply intertwined and dependent on each other's presence (Yoo, 2010).

Previous research recognized that a particularly popular and personal experiential device with such intertwined self-tracking elements is the smartphone (e.g., Bødker, Gimpel, & Hedman, 2014). A smartphone is essentially an incomplete product until the user starts using and experiencing it by installing applications, surfing the web, taking photos and videos (e.g., Jung, 2014; Yoo, Boland, Lyytinen, & Majchrzak, 2012). The smartphone experience is highly individualized as "users decide what a smartphone is for themselves, rather than just adopting a given product" (Jung, 2014, p.300). Therefore, the rise of experiential computing is offering alternative values and user-empowerment beyond a traditional deterministic paradigm (ibid). The experience of the smartphone thus depends on the functionalities of the device paired with the interactions performed by the user, which means that the relationship with the device is potentially re-iterative and incomplete throughout the device's lifetime. The device is never static in its existence but is continuously shaped by the way it is used.

By using a smartphone, the user has the possibility to engage in self-tracking as well. For example, the camera creates a personal photo archive that documents a trail of experiences in picture form, which also include date, location and may even be able to tag people in the photos. These are all different types of experiential data that are collected by the experiential device. Another smartphone example is that the user can choose to download an application, e.g., RunKeeper, which tracks personal exercise activity and shows statistics such as duration, length of run and kilometer time. In both examples, the experiential device collects data about the user's experiences and allows him or her to "explore the data by following their own personal interests within the context of an event" (Jain 2010, p.49). This self-tracking activity can result in both qualitative and quantitative experiential data that is more or less deliberately collected by the user.

2.3 Self-tracking as the activity of collecting personal data

The activity of self-tracking is gaining attention from several disciplines beyond the technology centered focus, including medicine (Paton et al., 2012; Prince, 2014), where the patient's empowerment is particularly emphasized. It has also been recognized in educational efforts, where it might be valuable for both student learning and evaluation (Lee, 2013; Williamson, 2014). This research project adopts the term self-tracking as the main term, but other related terms exist, such as self-monitoring (Shilton, 2012), personal analytics (Williamson, 2014), personal informatics (I. Li et al., 2010), bio-hacking and lifelogging (Dodge & Kitchin, 2007).

The activity of self-tracking is data collection with qualitative and quantitative characteristics. A type of qualitative self-tracking, sometimes called lifelogging, involves the capture of data in photographic, video and audio formats (e.g., Dodge and Kitchin, 2007; Doherty et al., 2010). The outcome is a lifelog, which is similar to a personal archive, namely a type of digital record of an individual's life and experiences that assist in the retrieval of information and facilitates memory recall. Dodge and Kitchin (2007) propose that a lifelog is "a unified digital record of the totality of an individual's experiences, captured multimodally through digital sensors and stored permanently as a personal multimedia archive" (p.431). Another description is "a comprehensive archive of an individual's quotidian

existence” where the focus is “to create and preserve a complete and useable record of one's own life” (Allen 2008, p.73). Based on the above, the end goal is to have a total record of personal experiences throughout life that is available for immediate information retrieval. Lifelogging is viewed as a qualitative capture that creates a digital personal archive of user experiences gathered unobtrusively and automatically through technology.

The quantitative approach to self-tracking is called self-quantification. Self-quantification places focus on numbers in the narrower aspects of life experience, such as details of an event, i.e., the number of hours one slept during the night. Self-quantification practices goes “beyond remembering information about oneself; they focus on collecting data for the purpose of gaining self-knowledge through reflection” (Pirzadeh, He, & Stolterman, 2013, p.1980). Instead, self-quantification is about analyzing everyday activities to help improve life. Self-quantification is popular in the movement called the ‘Quantified Self’ that gather enthusiasts in pursuit of “knowledge through numbers”. One of the founders, Wolf (2010), explains that managers, practitioners and private people are attracted to the power of numbers due to the seemingly rational and objective nature they hold. Wolf (2010) even asserts that self-quantification helps users gain insight on issues that they might not have thought of yet, thus suggesting that numbers can aid understanding. Self-quantification can also have a more action-oriented perspective, as Swan (2013) suggests: “the key reason individuals conducted some sort of Quantified Self project was to resolve or optimize a specific lifestyle issue” (p.238).

With the selling points of taking charge, getting motivated and leading a healthier lifestyle, self-quantification tools are rising in popularity. The continuous miniaturization of IT artifacts with sensors and with more processing power is also attractive to users, resulting in activity trackers like Fitbit and Jawbone UP. Such self-tracking wearables enable personal data capture that go beyond photos, videos and text and offer accessibility to quantitative data.

Self-tracking can be primarily divided into two types of data collection, life as a whole and the component aspects of life. In the former and often more qualitative data collection, the purpose is to document everything in life to enable future retrieval. The personal archive is a type of storage that is meant to act as a support

memory aid (Doherty, Moulin, et al., 2011). This is often related closely to the activity of lifelogging (Arcega, Font, & Cetina, 2013). Alternatively, more practical aspects of life are also tracked, such as physical performance and sleep. The self-tracking, it is argued in this dissertation, has potential to support future action such as self-reflection and behavioral change (DiClemente et al., 2001; I. Li, 2012). As opposed to whole life tracking, the tracking of smaller aspects often engage the users more actively and frequently (Doherty, Caprani, et al., 2011).

Self-tracking is usually done manually or automatically, but both processes may occur at the same time depending on the type of data collection. Manual self-tracking can be done with tools such as pen and paper, desktop spreadsheets, or entering data into mobile applications. For example, Moodscope is a mood-tracking platform where the user logs in to a personal account regularly, answers 20 questions and is given a score from 1-100 on a scale. Manual tracking often requires more attention and engagement from the user than automatic self-tracking (Consolvo, McDonald, et al., 2009).

Manual logging is often considered to require too much effort, which makes the user log less often, creating less consistent data, or even leading the user to abandon the self-tracking altogether (e.g., Pirzadeh et al., 2013). On the other hand, several studies debate how to include manual input when manual logging does not occur frequently and systems prompts can be intrusive (Bentley et al., 2013). Research proposes status bar reminders are more effective, as opposed to push notifications or text messages (Bentley et al., 2013). This is due to a spillover effect in which users viewed the data more frequently and then “walked away with a lasting understanding of the factors that impact various aspects of their wellbeing” (p.30:21). Even when users do not manually log data, there should be an option to manually edit and delete data, which is not always permitted in popular products (Consolvo et al., 2008; Jain, 2003). For example, the app Moves tracks the user’s daily movement patterns, such as walking, biking, and driving. However, it is not possible to add or delete any of the data that is collected. Manual logging is thus preferable because it “improves the credibility of an imperfect system” (ibid, p.1805). In addition, the users “stated that they felt an “intimacy with data” when they tracked the data manually” (Choe, Lee, Lee, Pratt, & Kientz, 2014, p.9). Manual functionalities are thus important for several aspects

of the relationship between the user and the data, including credibility, understanding and trust.

On the other hand, automatic self-tracking occurs unobtrusively and does not need active input of the user to gather data. Instead, the user typically uses a tool that automatically gathers data on the selected area of interest. This is often done by using wearable technology, such as fitness trackers that have sensors that read the physical performance of the person that is carrying the device on them. For example, the Jawbone UP automatically tracks the steps and sleep patterns of a person.

The inability to edit and delete either manually or automatically collected data has implications for the private nature of self-tracking data. The better and more encapsulating the technology becomes, the more significant the privacy issues also become (Allen, 2008; Dobbins et al., 2014). The concerns range from the user's privacy to the users who accidentally are included in data collection (Fitzgibbon & Reiter, 2003). Allen (2008) states that the "very ideas of 'past' and 'present' in relation to personal information are in danger of evaporating. The past is on the surface, like skim" (p.62), which means that the value of forgetting does not exist and that the past is practically inerasable (Fitzgibbon & Reiter, 2003). The user's protection against invasion of privacy is through awareness of what is being tracked (O'Hara et al., 2009). Others are not particularly concerned with privacy due to noise, or low resolution of the images and infrequent capture, since it makes it difficult to identify any users who are unwillingly or unknowingly captured (Hodges et al., 2006).

The pursuit of self-tracking has emphasized the importance of unobtrusive and automatic data capture that allows the user to go about business as usual (e.g., Czerwinski et al., 2006). The objective is to be able to offer user devices that are effortlessly included in everyday life, while still capturing life experiences. In this respect, self-tracking should be "the digital capture of a person's everyday activities, in an unobtrusive and passive fashion" (Doherty et al., 2012, p.153) because it is "the process of automatically recording aspects of one's life in digital form without loss of information" (ibid, p.151). Therefore, it should not include deliberate activities that involve laborious and selective personal capture of data.

Instead, self-tracking “seeks to be effortless and all-encompassing in terms of data capture” (Sellen et al., 2010, p.72).

Self-tracking in this research emphasizes the inclusion of technology to enable this activity. Nevertheless, the existence of non-technological self-tracking activities that involve spreadsheets and journaling is recognized, though not investigated. Self-tracking can also take place without the explicit and conscious contribution of the user, e.g., when a website tracks the behavior of users. In this case, the tracking is not understood as self-tracking but as general data collection by a third party. Tools for self-tracking are those that users consciously choose to engage in a specific activity that involves personal data collection.

Next to the core premise of self-tracking activities, other research investigates the potential outcome of this activity, namely the personal data archive. The digitalization of a personal archive emerged as a discussion to collect for the purposes of memory aid, and has grown into considering premises for its possible implementation, restrictions, maintenance and duration. The next section discusses the development of the personal archive.

2.4 A personal archive of personal data

The recording and collection of personal experiences for the purposes of a personal archive is by no means a novel practice. Cave drawings, portraits, paintings, memoirs, letter correspondences, diaries and libraries—these are all different types of personal archives that have been part of the human experience. The creation of a personal archive has now been further enabled with the development of technology (Dodge & Kitchin, 2007; Gemmell et al., 2006). The personal archive stems from a computer and software design perspective where the aim of creating a digital index was researched by building and testing prototypes (e.g., Bell & Gemmell, 2007; Gemmell et al., 2006; Mann, 1997).

In an example from the early days of computing, Bush (1945) proposed the development of a personal archive that would index different types of experiences that could be used for personal retrieval in the future. The proposition urged for a way to offset the inevitable failing memory human beings experienced by the development of new technology and argued that “instruments are at hand which, if

properly developed, will give man access to and command over the inherited knowledge of the ages”(p.35). The tool to enable this was called Memex. Memex was seen to be a “future device for individual use, which is a sort of mechanized private file and library” that would store any desired record, such as books and communications, rather than keeping these as physical artifacts (ibid, p.43). This process of handling information supported the argument that “man's spirit should be elevated if he can better review his shady past and analyze more completely and objectively his present problems. He has built a civilization so complex that he needs to mechanize his record more fully if he is to push his experiment to its logical conclusion and not merely become bogged down part way there by overtaxing his limited memory” (ibid, p.46). Bush envisioned possibilities of creating an externalized personal archive long before the existence of current technology. As technology has advanced, the vision of a personal archive still remains a sought-after goal as much as a contemporary challenge, as is acknowledged in studies over the past decades.

Others have followed in the vision of a paperless and technology-enabled personal archive. Bush’s vision was limited by the state of technology at the time but contemporary technological advancements make the personal archive a reality. The digital extension of the user’s memory is now fueled and created by using various systems and tools, which involve advanced sensors, processors, and cameras (Bell & Gemmell, 2007; Dobbins et al., 2014; H. Lee et al., 2008; Sellen et al., 2007). In the pursuit of a paperless future, Bell presents the concept of “CyberAll”, which is described as a type of personal digital store. Cyberall is meant to “encode, store, and allow easy retrieval of all of a person’s information for personal and professional use” (Bell, 2001, p.86). This archive is meant to be a memory aid for the individual, because Bell believes that memory is likely to fail due to increasing exposure to information. The increased amount of information causes information overload (Bawden & Robinson, 2008). An extensively studied implementation that enabled creating a personal archive is MyLifeBits (Bell & Gemmell, 2007; Gemmell et al., 2006). The project of MyLifeBits advanced over six years of studies and showed that digital memories like sound and images did elevate general reflection, self-reflection and serve as a memory aid. Allen (2008)) and Hodges et al. (2006) also state that using a retrospective memory aid will help improve access to memories. Additional studies on memory aid through personal

archives have been done (Fitzgibbon & Reiter, 2003; Lahlou, 2008; O'Hara, Tuffield, & Shadbolt, 2009; Sellen & Whittaker, 2010).

Despite the vast development in technology, there are still concerns and shortcomings related to the abilities of users to maintain a personal archive over a longer period of time. For example, Fitzgibbon and Reiter (2003) argue that the possibilities of a personal archive are halted by the limitations of technology when it comes to “managing enormous, heterogeneous, and continually expanding information repositories” (p.5). Yet, they believe that as soon as technology is more advanced it will be possible to extract and use data that will in turn build more intelligent tools. However, although technology might be able to collect more data in the present, there is still considerable concern regarding the potential lifespan of using such data. A main concern is that data will not be accessible because of the evolving nature of the formats in which data is stored (Jain, 2010). The likelihood is that hardware and software will change frequently over time, so it is important that the data outlasts the systems that process it (Fitzgibbon and Reiter, 2003). Bell (2001) also discusses the different formats and their possible endangered life expectancy by comparing it to the 8-track tape. He suggests that “[i]nformation must be held in a few golden primitive formats because these have to be supported forever” (Bell, 2001, p.89). Gemmell and Bell also make a main point of this issue because “We have already run into cases where we could not access documents because their formats were obsolete” (p.65). However, this issue is already present as the use of different applications may lead to different types of data, causing “issues for formatting”. (Li et al., 2010, p.560). For example, mobile apps developed for iOS smartphones cannot be used in Android smartphones, which also creates different types of data that is often not transferable. The literature therefore suggests that the system should be flexible in supporting different types of import and export of data.

The purpose of the personal archive has changed over time. Early studies (e.g., Bell and Gemmell 2007, Gemmell and Bell 2007; Mann 1997) suggest that the primary concern was to be able to capture and store data, followed by the objective of being able to retrieve data as a help to memory. The former purpose was to have a personal archive for memory retrieval that could help generate reflection about an event or experience that the user had participated in. Such retrieval is focused on the past, by accumulating as much data as possible on the

present. However, later studies indicate that the most important aspect of a personal archive is to foster some type of introspection, e.g., self-reflection (I. Li, 2012), self-awareness (Bentley et al., 2013), and behavioral change (J. J. Lin et al., 2006). The predominant notion is that the use of experiential devices for the purpose of self-tracking personal data has as a goal to “reflect upon one’s data, extract meaningful insights, and make positive changes, which are the hardest part” (Choe et al., 2014, p.1152). There is a stronger emphasis on the self and the personal, which has developed into a type of personal management (Fitzgibbon & Reiter, 2003). In this respect, the purpose of the digital personal archive has shifted from retrieval of the past to self-reflection and behavioral change in the future.

This section focused on the technological capabilities to transform the activities of self-tracking into a tool—the personal archive. The personal archive may have various shapes and formats but it is ultimately an index of personal data. The discussion centers on the technology’s various functionalities for the future and their impact on the user, though it is not intended to address a deeper understanding of the user’s reactions to the data. Along with the focus on a data archive, other research investigates the user’s reactions to the exposure of the data archive and the resulting interpretations and behaviors. The technology’s design of exposing data intends to lead to engagement from the perspective of technology, yet the process of engagement encounters obstacles. These obstacles are presented in the next section.

2.5 Exposure and engagement with personal data

The user’s exposure and engagement with the personal device and subsequent data output is a multifaceted matter where the possible expected outcomes, such as self-reflection, self-understanding and behavioral change, as well as their magnitude, are debated in the literature as well as in this section. In particular, this research context focuses on how engagement leads to introspection in the form of self-reflection, instead of reflection on matters that neither involve nor relate to the user’s sense of self. This focus is based on the premise that the experiential devices collect personal data, turning the focus towards the personal experience of the individual. The process of self-reflection is often underlined as important because the user can gain self-awareness, self-understanding and as stated

previously, even change behavior (e.g., Hultgren, Wiggers, & Jonker, 2014; Khovanskaya, Baumer, Cosley, Volda, & Gay, 2013; Li, 2012). Therefore, the process of self-reflection plays a significant role in discussions of self-tracking practices through experiential devices because it both spurs on and halts self-reflection. Due to the nature of self-tracking, the context is tied to psychological studies on introspection (Hixon & Swann, 1993) that has been applied frequently to human and computer interaction (I. Li et al., 2011).

The exposure and engagement with the data occurs during or after the data has been collected through an experiential device. In studies stemming from earlier days of digitizing personal archives, the engagement was sporadic and often prompted by a specific trigger, such as when attempting to retrieve details of a certain life event (Doherty et al., 2011). This was mainly because the retrieval was difficult, since the archive was often organized with a stationary computer and software (Gemmell et al., 2006). However, many current and more advanced self-tracking devices offer the possibility of instantaneous feedback from the collected data due to their ubiquitous nature. The self-tracking devices are worn on or close to the body and sometimes have displays, or they are synced with a smartphone. This makes it possible for the user to be instantly exposed and engaged with the data. For example, a user may watch the heart rate monitor while running. The objective is to get the user to engage as much as possible with the device because increased use reinforces the output of the device—the data and its continued use it in the future (Bentley & Tollmar, 2013).

The collection and subsequent exposure and engagement with personal data may be considered as a type of personal self-management (Fitzgibbon & Reiter, 2003). In the above sections, the outcome and activity of self-tracking suggest that the personal data is gathered for the purposes of informing the user for self-reflection and behavioral change (Bentley et al., 2013; I. Li et al., 2010). The activity of self-tracking “augments a person’s self-knowledge by breaking down human barriers to personal data management” (Khovanskaya et al., 2013). In an ideal self-management scenario, the user collects a relevant yet substantial amount of data through an experiential device. As soon as the data collection is opened and exposed to the user, the user is instantaneously aware of personal patterns of action and behavior. This gained awareness then triggers the process of self-reflection, which is iterative and ultimately leads to increased self-understanding.

All of this means that the user can become a better self-manager who can make smarter and more effective decisions (Cosley, Sosik, Schultz, Peesapati, & Lee, 2012). However, the actual scenario is likely not to be so straight forward, but instead to be subjected to cognitive biases and barriers throughout the stages of the data collection, the data organization, self-reflection and any subsequent intent of behavioral change. This aspect is one which explores the role of the user after exposure and in engagement with the personal data.

Influenced by related literature, this section also places a focus on the system and any related devices, much like the previous section on the capabilities of collecting a personal archive. The forthcoming section presents the different perspectives that the user encounters when engaging with the personal data for the purposes of self-reflection and subsequent changes in behavior.

2.5.1 Perspectives on engagement with data for self-reflection

After engaging in self-tracking for personal data, the user is exposed to the data, which has both advantages and disadvantages for self-reflection. The term self-reflection is continuously used by academics as the ultimate goal of the self-tracking user, yet it is loosely defined in the literature. One definition states that self-reflection has the goal “to reflect upon one’s data” and “extract meaningful insights” (Choe et al., 2014, p.1152). Another example is the statement that self-reflection is presented as the attempt to “interpret and reflect on the data about their physical activities” (Consolvo et al., 2008, p, 1797). For this example, a running enthusiast regularly checks his or her running data through a mobile app, such as RunKeeper, and may find that the pace is quicker in the first kilometer than in the last kilometer. In this specific context, the literature points at self-reflection as an activity where the user draws objective conclusions from the personal data that has been collected. However, more specifically, self-reflection is understood as a type of introspection where the user assesses the self and any related abstract or concrete activities, such as mood or physical activity (Hixon & Swann, 1993). The reflective process is thus meant to make unconscious aspects more conscious to the user (Huldtgren et al., 2014). Self-reflection is therefore understood as the user’s introspection to become more conscious of unconscious aspects, accessing the subjective information with the help of personal data.

The road to introspection is complex and difficult to identify, analyze and evaluate (Cosley et al., 2012; Hixon & Swann, 1993). While the ultimate goal is to engage in self-reflection for personal insight, the outcome does not always match the goal. There are studies that have found self-reflection can disrupt performance, especially if the reflection is regarding ordinary tasks that are usually thought of as automatic (Howard & Ballas, 1980; Reber, 1989). It has also been suggested that self-reflection undermines an individual's insight into his or her own behavior. This means that a user may be able to reflect on the self and even provide an explanation for it, yet this explanation may not be accurate (Nisbett & Wilson, 1977). Instead, it is the "the result of thinking, not the process of thinking" that the individual remembers and can convey (Miller, 1962, p. 56). The product of thinking is thus clear to the individual, yet not the process of reflecting and constructing this product (*ibid*). These theoretical arguments propose that self-reflection is indeed a complex arena both for the user as well as the researcher. In this section, self-reflection is discussed in relation to the user's exposure and engagement with the data.

The exposure to personal data is argued to be valuable to self-reflection, but also counterproductive. These opposing perspectives are continuously debated. The predominant assumption in the examined literature is that the exploration and engagement of personal data influences and increases self-reflection which might lead to insights (Blum, Pentland, & Tröster, 2006; Hixon & Swann, 1993; Hultdtgren et al., 2014; I. Li et al., 2010; I. Li, 2012; Pirzadeh et al., 2013). External input, such as personal data, benefits the user and it becomes an aid for memory, reflection and decision (Bush, 1945; Gemmell et al., 2006; O'Donoghue & Rabin, 2003), as human knowledge and memory is rationally bounded (Simon, 1955; Kahneman, 2003b;). The self-reflective process can spur different intentions in different types of users, such as wanting to confirm what was already known versus wanting to gain new knowledge (Hultdtgren et al., 2014). The more transparent the data, the more the user is able to thoroughly evaluate it (Blum et al., 2006; Jaimes, Murray, & Raij, 2013). Despite the overarching emphasis on the importance of exposure to data for self-reflection, studies assert that many systems do not sufficiently support the user in this endeavor (Khovanskaya et al., 2013; Mamykina & Mynatt, 2008; Ploderer, Reitberger, Oinas-Kukkonen, & van Gemert-Pijnen, 2014). In particular, the system does not support exploration and experimentation (Jain, 2003), nor provides transparency as advised (Khovanskaya

et al., 2013). This leaves the user with a personal archive and a desire to engage, yet without the tools or knowledge of how to do so.

On the other hand, the engagement with personal data may lead to a decline in self-reflection and intuition, according to some research (Williamson, 2014; Choe et al., 2014). In this case, the user does not reflect on the experience that is mediated through personal data, but merely just reviews it without reflection or criticism. For example, Williamson (2014) argues that the prospect of incorporating tracking technologies is likely to produce in-depth albeit anonymous predictions of human behavior. These data based predictions will proceed to shape and govern users and social groups where the individual is “redefined as a kind of software that has been made amenable to being acted upon, enhanced and optimized, as instructed by codes and algorithms” (p.148). These systems are believed to be threatening because they devalue the softer and emotional evaluations, such as reflection and intuition. These competences will deteriorate, since the system will provide insights for action. Choe et al. (2014) suggest that automatic self-tracking is a main perpetrator in reducing awareness and self-reflection.

The engagement with data is more difficult for some users and stops the possibilities for exploring self-reflection through the data. Some users dislike independently engaging with the personal data for the purposes of self-reflection, for it makes them uncomfortable, but respond better to this through a system-fabricated support. In the example of a diabetes dashboard for newly diagnosed patients, the users preferred engaging with the data and reflecting when they had the support of a professional to train, instruct as well as present conclusions of the data for them. The users found the dashboard helpful, but preferred the assistance of an additional person to share concerns and validate any pending insights. The inability or reluctance to engage in self-reflection through the interpretation of personal data is a common occurrence throughout the literature (Cosley et al., 2012; Lupton, 2014). However, studies predominantly underline the opportunities and alterations that the system provides to the user’s self-reflective process by presenting data visualizations and features, rather than portraying the depth of the user’s issues with the engagement (e.g., Consolvo et al., 2008; Cuttone, Petersen, & Larsen, 2014; Moradi & Wiberg, 2013).

The ambiguous role of experiential devices for individual interpretation and experiences remains an interesting research domain, one which motivates this project and it is further expanded and explored in this section. There is an opportunity to contribute to research on how engagement with personal data followed by seemingly ad-hoc perceptions influences the process of self-reflection. In this respect, the engagement with personal data might or might not instigate self-reflection, yet the topic proves appealing for further investigation to analyze what occurs during and after self-reflection. To further visit this inquiry on user engagement for the purpose of self-reflection, the key models of engagement for self-reflection in a self-tracking context are presented below.

2.5.2 Models of engagement with data for self-reflection

The process in which self-reflection emerges through engaging with self-tracking data is multifaceted. It is often described as a part of a chain of events rather than isolated in occurrence (Karapanos, 2013; I. Li et al., 2010; Pirzadeh et al., 2013). These events or stages might be anything from preparing and collecting data to making decisions. The different theoretical frameworks related to self-reflection through self-tracking activities are presented below.

One model involves three stages of self-reflection, according to a digital journaling study (Pirzadeh et al., 2013). In the first stage of reflection, the user gains awareness of the self through viewing the data. This is followed by critical analysis where the user considers past sequences to gather information and then to analyze the present situation. In the last stage the user may develop a new perspective, which might eventually lead to changed behavior. The proposed model aimed to contribute to the understanding of the reflection stage while self-tracking (ibid). However, the framework is primarily concerned with manual self-tracking, such as writing notes, which makes the user intertwined with the data continuously while tracking. In a different scenario, such as automatic self-tracking, the experiential device collects the data in the background without the same continuous participation of the collection. In the automatic tracking, the user is usually exposed to data and engages after the data has been collected, rather than during. Therefore, the framework showcases an overarching process proposal, but it does not address any differences nor implications that may arise when collecting data manually or automatically. The user that has continuously been manually self-tracking is likely to have a stronger degree of familiarity with

the data than the user who has left the self-tracking to an automatic device; this influences the process of awareness and reflection on the personal data. Furthermore, the model assumes an ideal scenario and does not address outcomes if the user fails to live up to the characteristics of the stages.

An alternative model distinguishes four stages: awareness, reflection, sensemaking and impact (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). At first, the emphasis is on the visualization of the data that is expected to give the user awareness. This is followed by reflection where the user poses questions and examines the data for relevance and value. After relevance has been determined, the user attempts to make sense of the data by answering the questions, which is suggested to foster insight. Finally, the impact of the sensemaking is meant to “induce meaning or change behavior if the user deems it useful to do so” (ibid, p.2-3). The framework pinpoints relevant steps that the user goes through after being exposed to the personal data. The steps are explained briefly and would benefit from further elaboration in different scenarios. As in the previous example, the framework does not provide an explanation to what occurs if the user fails at any stage. For example, there is no discussion on what occurs if the user poses irrelevant questions and cannot answer these questions by him or herself. As a result, the framework is valuable as an ideal path for the user but does not offer further understanding of the relationship between the user and the system.

Another proposal that describes the user’s experiences with personal device and data introduces three stages called orientation, incorporation and identification (Karapanos, 2013). In this framework, reflection occurs during all stages and evolves from being rationally bound to being emotionally bound to the device and the data. In the first phase, orientation, the user explores the device and the data. The user first wants ease-of-use, but over time usefulness becomes the main predictor of continued use. After that, incorporation occurs, which means that the user is prone to develop an emotional attachment to the experiential device, which in turn increases use. Lastly, the framework suggests that the increased emotional attachment leads to identification that solidifies the use. Identification also increases when the device strikes a balance between being ubiquitous and adaptable. This trait is particularly relevant when it comes to experiential devices because the device is often inherently both personal and ubiquitous in nature. The framework illustrates how reflection evolves alongside the interaction with the

data and creates a new relationship and user pattern between the device and user. The focus is on the outcome of use. At the same time, it does not explain how or to what extent the user interacts with the data but only that the relationship evolves.

The user's self-reflective stage can also be surrounded by other influencing stages between which reflection occurs. In a stage-based model, the stages of preparation, collection and integration comes before reflection, which is then followed by action (I. Li et al., 2010). The stages affect one another in a cascade, so the choices made early on might influence later outcomes. In this way the reflection stage is not static but may also spill over to other stages both before and after. The reflective stage is characterized as explorative and it is where the user gains understanding of the data. The user may not gain these benefits if he or she has "difficulties retrieving, exploring, and understanding information" (ibid, p.562), such as not being able to derive value from visualizations. This also inhibits the user from transitioning into the next stage that could involve behavioral change. The model is valuable in that it identifies in more detail the components that make up the self-tracking process and how these influence each other.

The Li et al. (2010) stage-based model has been criticized for being too technology-centric (Rooksby & Rost, 2014) because it assumes that any issues such as self-reflection can be resolved by adopting or adjusting the system. Instead, Rooksby & Rost (2014) claim it is "unrealistic to assume that people can or want to do rational data collection, and act only when data has been validated and thoroughly analysed" (p.27). This perspective invites the prospect to pursue a more user-centric investigation of how the self-reflective stage unfolds. Others who have emphasized this are Hultgren et al. (2014)—they include cognitive and emotional characteristics of human decision making in their work on self-tracking.

In this section, the emergence of self-reflection is presented through different perspectives and how they treat the interaction between a system and a user. The frameworks offer insights on the multifaceted process that occurs when the user is exposed to the data captured by self-tracking related activities and devices. Pirzadeh et al. (2014) emphasize the reflection of output, Verbert et al. (2013) suggest that impact rather than behavioral change is valuable, Karapanos (2013)

places weight on device interaction while the Li et al. (2010) model proposes fluid stages between which reflection fluctuates. The focus of the contributions varies but there are common points as well. The principal similarity lies in the premise that the framework starts with some type of exposure to data, followed by immediate awareness that leads to a deeper reflection and eventually some type of positive change, such as attitude or behavior optimization.

However, as discussed above, the user's needs are complex. Experiential computing suggests that the user does not only use the device for traditional performance tasks but for a range of informational and social needs, which causes the use to continuously change (Yoo, 2010). The models above take into account the ideal process that the system can offer to the user, but do not present a nuanced portrayal of the potential re-iterations or pitfalls that might occur between the two. For example, the frameworks do not touch upon whether the user to some extent rejects the data as valuable or helpful. In such a case, questions arise on how reflection and behavior are impacted. Therefore, the above frameworks offer a perspective where the user has a continuous and almost linear approach to handling and analyzing the personal data.

This research project assumes that the user and technology are dependent on each other to capture the experience that lies between them (Yoo, 2010), yet the above frameworks do not address this relationship. Instead, these frameworks depart from a predominantly technology-centric perspective, where the user is included in the process but often secondary to the outcome. The user's experience is instead suggested to be shaped by the technology, rather than focusing on the experience that lies between the technology and the user. This research project intends to address this gap by further exploring the perspective of the user and how he or she reasons in relation to exposure and engagement with the personal data.

The next section presents design features that it is argued can improve a self-tracking system's functionalities to support engagement with data for self-reflection.

2.6 Striving to support engagement for the purpose of self-reflection

The activity of self-tracking can support self-reflection with help from engagement with the technology as it creates value for the user. In the pursuit of supporting self-reflection, several studies focus on optimizing the technology and system interface by implementing features and design principles that are meant to cater to the user's needs. In this section, key categories are presented on how to address support of self-reflection in self-tracking systems. These categories were identified by reading the literature followed by summarizing features and design recommendations, and then by synthesizing the scattered recommendations into a set of categories. Many of the suggested recommendations in the literature are written under different names but have similar descriptions of effect and purpose and were thus merged under a common category. To the best of my knowledge, I have explored various streams and identified the key themes across the pool of literature related to self-tracking activities. The key themes are user identified as: user engagement with data, social engagement with data, personalization of data, visualization of data, and transparency of data.

2.6.1 User engagement with data

Self-tracking systems might benefit from including features that involve more user engagement (e.g., Consolvo et al., 2009; Li, Dey, & Forlizzi, 2012; Lin et al., 2006). The user's engagement strengthens the user's relationship to the data by providing a sense of ownership as the user is exposed to data. Two particularly reoccurring suggestions for user engagement are the inclusion of manual input and experimentation (Consolvo et al., 2008; Jain, 2003). By exploring and becoming more acquainted with the data, the user will be more comfortable and hopefully acquire skills and tools on how to address any abundance or insufficiency of data.

There are different ways of engaging the user with the data. For example, features that allows the user to add, edit and remove data (Consolvo et al., 2008) have been identified as relevant. In a study where the users wore activity trackers, the manual input allowed the user to be more familiar with the data through active interaction with it, and thus can "permit the individual to manipulate the data and give her control over who has access to what data" (p.409). This interaction is able to evoke a stronger sense of ownership through interaction with the data, rather than merely being exposed to it. The possibility of manually editing the data offers

a possibility for the user to engage more with the data, which in turn strengthens the relationship. This behavior was also observed in a journaling study where manual input, such as physically writing down information, created more engaged users (I. Li, Dey, et al., 2012).

Engagement can also be spurred on by possibilities for experimentation (Jain, 2003). The prospect of experimentation with the data invites the user to interact, analyze and play with the data, rather than taking it at face value, which might generate more self-reflection through viewing new perspectives. Unfortunately, many self-tracking users do not revisit the personal archive after the collection, but merely look at the latest data (Whittaker, Bergman, & Clough, 2010).

The user often needs to be reminded to engage with the system and the data. In the context of manual logging and experimentation, it is important to consider how it is introduced and what it demands from the user. In a study involving a food diary, the manual logging was abandoned after a few days. This was due to tracking fatigue (E. K. Choe et al., 2014; Pirzadeh et al., 2013). In the same study, the remedy for this was to send notifications that served as reminders to log data. This increased the engagement from 12% to 63% (Bentley & Tollmar, 2013). In a system that places weight on manual logging as the main form of data collection, it is essential to consider how the user is going to maintain this interaction. The possibility to manually perform edits is also a way to overcome any pending limitation of the IT artifact's data collection capabilities. This means that if the device has collected any faulty data, the user can correct it. The ability to collect the correct information is important to the trust of the user as well as increasing engagement.

2.6.2 Social engagement with data

The incorporation of social elements offers a system support structure for the user to share concerns as well as to become inspired by others' data. The exposure to other types of data might encourage comparison and competition, but also serve as a motivation to continue for the purpose of social approval and desirability (Adams et al., 2005; Tajfel, 2010). The user attempts to identify with a social group but at the same time to distinguish him or herself within this group for positive self-esteem (Hogg, 2000; Tajfel, 2010). Thus, the user's self-reflective

process can be supported because of the ability to share information and become part of a context (Froehlich, 2011; Hultgren et al., 2014). In this way, a social presence is thus believed to “support change and shape attitudinal and behavioral responses” of the individual user (Comber and Thieme 2013, p.1197). The inclusion of social needs (Consolvo, McDonald, et al., 2009) through friends or professionals (Mamykina & Mynatt, 2008) may cause different types of engagement that both have been suggested to increase self-reflection.

Social engagement that increases reflection and behavioral change should stand on five components, such as social traces, social support, collective use, reflection-in-action, and reflection-on-action (Ploderer et al., 2014). Social traces are meant to give a normative influence that brings both comparison and competition. Social support is the exchange between users to give and receive support and advice. The focus on collective use signifies that a shared space is a stronger space. Reflection in- and on-action refers to reflection support prior and post an activity. This framework gives valuable proposal in how to design for increased reflection and behavior change.

Social influence has an impact on a user’s motivation and behavior. In an example, the mobile app Chick clique invites teenage girls to exercise more and found that data sharing and group performance was the most powerful motivator toward action and movement (Toscos et al., 2006). In another study involving the application BinCam, the recycling habits of users were investigated (Froelich et al., 2010). The participants of the study installed BinCam and attached it to respective Facebook pages. Then BinCam monitored the user’s recycling habits and the Facebook page shared this progress with the rest of the recycler’s network. The study found that when the user was not acting according to his or her intention, guilt emerged because of the audience “watching” in the social network. Therefore, the user reflected on the rising negative emotion of the audience and changed the behavior in order to achieve a more sustainable response. The study concluded that self-reflection, even if it is a reaction to social influence, is important because it changes the attention and cognition of habitual behavior, which leads to mindfulness of inappropriate behavior. These findings are similar to those of the study Fish’n’ssteps, where the users experienced guilt due to exposure in a social setting (J. J. Lin et al., 2006). At the same time, the social setting also spurred competition and the ambition to perform better than others

(ibid). A social network may also influence self-control issues that a user may have when it comes to adapting new behavior, such as accepting awareness of the self and behavioral change (O'Donoghue & Rabin, 2003).

2.6.3 Personalization of data

Self-reflection can be supported by a system that offers a personalization of the user's data. This refers to the system's organization, analysis and presentation of a personalized summary of the personal data to the user. This type of system support is believed to be valuable as it sorts the abundance of data into a more overarching summary that the user can grasp. The recommendation is often repeated in the literature as a remedy to the fact that the user has difficulty in digesting and processing the persona (E. K. Choe et al., 2014; Hultdtgren et al., 2014). The overwhelming amount of data causes an information overload and is a recurring issue for users of IT systems (Bawden & Robinson, 2008).

Therefore, system guidance can be helpful to inspire the user to explore and interact more with the data (Adomavicius & Tuzhilin, 2005; Bentley et al., 2013). Personalization can entail a variety of different features in the system design, such as push notifications and graphs. In essence, personalization means that the system provides the user with processed information based on the user's personal data history. One example is sending status bar notifications. A notification system that sends a personalized status bar message about the user's behavior, such as "on Wednesdays you walk less than rest of the week" helps the user understand the data better by highlighting patterns. The status bar notification is less intrusive than a push-notification or a text message, and therefore remains a more welcome input (Consolvo, McDonald, et al., 2009). Such notifications make it easier for the user to be aware of problematic areas of behavior (Bentley et al., 2013; Bentley & Tollmar, 2013). In the study, the status bar notification helped the user gain awareness and self-reflection that led to a general well-being, such as making healthier food choices, subsequent weight-loss and mood improvement. On the other hand, a personalized message might be equally abrupt for introducing actionable advice. Medynskiy and Mynatt (2010) go so far as to assert that the user needs more focus on how the data can become actionable rather than actionable advice, so that behavioral changes can occur. This is helpful because current systems only provide visualizations and data aggregation to a certain

degree, yet the users are often left to interpret the data independently and without much support on how to incorporate actionable options. There are also others who agree that users can be hesitant towards recommendations based on system algorithms (Komiak & Benbasat, 2006).

Personalized insights could include customized recommendations for a specific user, yet this highlights a difficult area to address due to a ‘semantic gap’ between technology and the user (Doherty et al., 2012). It is proposed that the “next computational/technology challenge lies in semantic interpretation and search” (ibid, p.169). The next step is thus for technology to be able to translate the data collected into meaningful insights that are delivered to the user. This gap likely arises because the significance of personal data is a highly subjective matter, meaning that only the individual can evaluate the weight of a data point about him or herself. However, some research asserts that algorithmic decision making is superior to human judgment because individuals are prone to inherent biases (Hodgkinson, Maule, Bown, Pearman, & Glaister, 2002). This suggests that technology is more adept at evaluating data because individuals cannot stand outside his or her own emotional or subjective view on the data. Although, this is a double-edged sword as the system’s algorithms reduce the possibility for the user to engage in the full set of data, which may inhibit possible self-reflection as well (Jaimes et al., 2013; Khovanskaya et al., 2013). The data is meant to be personalized, yet it leads to narrower choices (Newell & Marabelli, 2015).

On the other hand, applying analytical effort can also be overwhelming for the user, who may then not be able to organize and analyze the data on his or her own (Whitaker et al., 2012). Some users may not arrive at the point where they are able to analyze the data at all, rendering the data merely an archive, rather than a consulting resource. For example studies conducted by Petrelli & Whittaker (2010) and Whittaker et al. (2010) show that digital mementos, such as photos, are perceived as less valuable and are not accessed by the owner when compared to physical mementos. This is because the digital collection is unorganized and not well integrated into everyday life and therefore locked into a computer where they are forgotten and can lose value.

2.6.4 Visualization of data

The visualization of data is a general concern and point of contention throughout the literature. The visualization of the data addresses how the data is represented by the system to the user, for example, by presenting the personal data as a timeline, showing graphs in the interface or comparing different variables, such as sleep quality versus training. Studies agree that there is a need for a stronger conscientious design of the data, and the key remedies identified in the literature are reviewed in this section (Consolvo, McDonald, et al., 2009). The common outlook is that design of the system's data exposure must support the user's ability to be reflective of a particularly vast data collection. If the visualization is not easily interpretable by the user, it is more difficult to engage in meaningful self-reflection. This does not mean that the user does not already have access to the data, just that it might not be the right kind of data (I. Li, Dey, et al., 2012).

The visualization of the data should also keep a close proximity between the device, the user and the translation of data categories. For example, users who had an easily interpretable display close at hand, such as on the mobile, were better at maintaining awareness, as well as maintaining any potential behavioral change (Consolvo et al., 2008). Cuttone et al. (2014) support this notion and state that "users want to obtain answers to a question with the minimal effort and time"(p.544), which is why the system should give a "swift overview of personal tracking activities, and to augment and support subjective recollection" (p.545). Therefore, the design should be filtered and not raw, and promote unobtrusiveness while maintaining an aesthetic that is publically pleasant (Consolvo, McDonald, et al., 2009; Jafarainimi, Forlizzi, Hurst, & Zimmerman, 2005). Moreover, Froehlich et al. (2010) also assert that it is critically important that the designers of any system understand the context and continue to design the visualization with such motivation in mind. For example, when tracking ecological behavior such as water consumption, the daily usage should be visualized alongside general recommendations for being more efficient, such as sharing how much money can be saved by installing a low-flow (p.9).

2.6.5 Transparency for trust of data

Transparency of the personal data is important to gain the user's trust for the system (Jaimes et al., 2013). In the context of self-tracking, the concept of

transparency means that the user should understand how the data is collected, analyzed, distributed and exposed through the tool (Huldtgren et al., 2014). However, this is not always clear to the user. Nevertheless, the system's interface has already gone through a filtering of the data for the purpose of reducing the complexity and providing personalization. This filter is meant to assist the user in increasing self-reflection and value from the data (Jaimes et al., 2013). However, personalization such as recommendations can foster hesitant users (Komiak & Benbasat, 2006). Instead, the element of transparency is meant to evoke trust and the user will be more inclined to interact and thus become more self-reflective. However, the risk of transparency is that there is too much information detail for the user to be able to handle.

Transparency and trust is closely related to privacy. For example, “an important element for personal memory technologies; users must be able to choose how much data they want to share with others” and therefore it is important to include user privacy settings that enable such transparency (Nishihata et al., 2012, p.103). For example, there could be the possibility to lock files for a certain time or limit visibility to certain data (Bell, 2001). Alternatively, an avatar could be created to work as a mediator between the individual and the data (O'Hara et al., 2008). Dodge and Kitchin (2007) considered the possibilities of designing for forgetting to “make the system humane and yet still useful”(p.442).

In summary, the engagement with data for self-reflection proposes five general categories to the system, which were listed earlier in section 2.5: user engagement with data, social engagement with data, personalization of data, visualization of data and transparency of data. These categories are related to system-centric features that have been designed to influence the user to continue using the device. These categories illustrate proposed remedies on how to update the system to support self-reflection. In the next section, the key challenges of supporting self-reflection are uncovered from a stronger user angle.

2.7 The challenges for supporting self-reflection

The key challenges in supporting self-reflection are identified as threefold: data engagement, data abundance, and data insufficiency. More specifically, data engagement is often inhibited due to data abundance or data insufficiency. The

user has access to data but does not perform an analysis of the data. These challenges are identified and conceptualized in the background of the self-tracking perspectives discovered in the literature as well as in the remedies of features that are put forward. There is a continued opening for discussion that this review of related literature has established, namely that the user's exposure to personal data does not automatically translate into self-reflection and self-understanding of lifestyle patterns (Bentley & Tollmar, 2013; Cuttone, Petersen, & Larsen, 2014; Dobbins, Merabti, Fergus, & Llewellyn-Jones, 2014). At the moment, the tools "are not designed with a sufficient understanding of users' self-reflection needs" (I. Li et al., 2011), which makes it "difficult for people to discover these long-term patterns about themselves" (Bentley, Tollmar, & Stephenson, 2013, p.30:2). In order to gain self-reflection for the purpose self-understanding, there is a need for more than mere accessibility to a wide archive—the user must be able to meaningfully engage with the data and derive conclusions from it (Mamykina & Mynatt, 2008). According to this perspective, the self-tracking systems do not accurately support self-reflection so that the user gets problems to analyze the data to make it meaningful.

As an overall departure point, engagement with personal data in the user interface can encourage as well as discourage self-reflection.

The abundance of data presents challenges for the individual's processing abilities (Bawden & Robinson, 2008). Dobbins et al. (2014) state that the search for the needed data within the personal archive is a key challenge due to the vast inventory of data that self-tracking activities gather. One reason is that the user has difficulties processing and organizing extensive entities of abstract data and turning it into concrete insights through self-reflection, which is why the user needs guidance that is divided up into several small steps (E. K. Choe et al., 2014; Hultgren et al., 2014). In another case, the users felt like the system was imposing values and requested to have more manual logging options (Consolvo, McDonald, et al., 2009). As a result, the data is gathered by the efforts of technology but the user has a personal archive that is not utilized because it is too complex to analyze (Whittaker, Bergman and Clough, 2010, p.38). This produces a dilemma, since the value of the collected data lies in the ability to be able to retrieve and analyze it.

Alternatively, some studies assert that there is insufficient data and advocate for more data to be included to support self-reflection. The general argument is that the data collection does not have the correct data points to derive insightful conclusions that can be reflected and acted upon (I. Li, 2012). Instead, the user wants and needs additional and different data. For example, the inclusion of context would benefit long term self-reflection (I. Li, Dey, et al., 2012) or triggers would benefit comprehension of context (E. K. Choe et al., 2014). Rooksby et al. (2014) supports the notion that insufficient data can be detrimental to self-reflection because “data can be meaningful in the context it is produced, but may lose meaning when it is removed from that context” (p.1172). Moreover, the visualization of data often reduces the complexity for it to be more accessible and understandable to the user, with the hope of increasing self-reflection (Jaimes et al., 2013). In this way, the perceived or prompted insufficiency of data may be resolved by the system’s visualization.

In both instances, an attempt to alleviate this concern and empower the user’s relationship of the personal data is done through transparency of shortcomings and uncertainty which is argued to help the user’s self-reflection (Henfridsson & Lindgren, 2005). Thus, the user should have the possibility to access, analyze and “to exert more control over their personal data, their public presence online and their digital identity” (O’Hara et al., 2008, p.171). Nevertheless, this resembles a circular argument because too much data as well as too little data makes it difficult for the user to process anything.

2.8 Towards an understanding of the user in the self-tracking process

This chapter reveals and affirms that there are variety of studies that have investigated several aspects of the implementation of experiential computing and how it might be altered to better cater to the utility of the user. The results demonstrate that current systems are well-developed and capable of capturing a range of aspects of everyday experience through advanced sensors and processors that did not exist before. A majority of the studies were concerned with “building systems to support factual recollection” (Whittaker et al. (2012, p.58). Sellen and Whittaker (2010) also substantiate the progress in technology that captures and collects data. This development also means that analysis and visualization of the

system's impact is more prominent than the user's perspective. The findings show that studies involving experiential devices have explored how to push the boundaries of technology and are successful in advancing the possibilities of practicing self-tracking. Altogether, these existing findings and future ambitions are yielding great discussion for the research around IT systems.

The activity of self-tracking in the pursuit of self-reflection is introduced from different angles to give a broader understanding for the research context. Self-tracking is conducted qualitatively or quantitatively, seeing life as a whole or aspects of life manually or automatically. This is followed by investigating self-tracking for the purpose of a personal archive. Then the aspects of engagement with personal data are presented, and the benefit from increased user engagement, social engagement, personalization, conscientious visualizations and transparency. As the chapter draws to its end, the context of self-tracking is linked to a set of key challenges that are summarized as abundance of data, insufficient data and visualization of data. These challenges were identified by exploring a system-oriented perspective, one which acknowledges the user, yet without interest in the user's perspective of the experience.

The challenges present a common concern for both the system and the user: a struggle to make sense of the personal data. The system perspective has difficulties in computing value from the data because the value embedded in the data is highly subjective (Doherty et al., 2012). The user perspective is also obscured due to difficulties in identifying the value of the overwhelming amount of data. In both cases, the desired outcome is to gain some kind of value from the data that the user can use for self-reflection, self-understanding and even behavioral change. This dilemma offers an opening for exploring the struggles related to making sense of the personal data. In doing so, a greater understanding is needed of the perspective and perceptions of the experience of the actual user (Yoo 2010). Therefore, a more human-centered approach, rather than a system-centered approach, would be valuable to continue the research discussion on extracting value from personal data (Sellen and Whittaker, 2010).

Experiential computing presents an opportunity to further investigate the relationship between the user, technology and the everyday experiences, rather than technology's role in influencing the user. However, the user's information

needs are both deeper and more complex since they reflect human needs and values (Yoo, 2010). The addition of a theoretical lens that embraces the user's perspective could broaden the investigation to include the user's experiences on self-tracking and the processes that are related to self-reflection on personal data. Therefore, this research project proposes incorporating a lens that allows the user's experience to be placed at the center and to do so by focusing on the user's processes of experiencing self-reflection. The application of behavioral economics provides such a perspective and has been done before in relation to information-rich environments and experiential devices, such as the smartphone. For example, a study of user behavior in rich information environments incorporated heuristics to understand decision processes in the choice of online content (Constantiou et al. 2012). Another study investigated the user's cognitive processes in relation to location-based services to understand how such processes influence information retrieval behavior. The study found that such a lens was useful to discuss cognitive processes and identify the value dimension for users (Constantiou et al., 2014).

The next chapter proceeds to uncover behavioral economics as a framework to understand and discuss the user's perspective when engaging in self-tracking activities.

2.9 Chapter summary

This chapter presented the theoretical background that is placed in the context of experiential computing. Thereafter, the activity of self-tracking is elaborated in order to specify the type of self-tracking that is examined more closely in this research. This is activity tracking with a focus on self-quantification. The outcome of self-tracking is a type of personal archive of past experiences and performances. Then the exposure to the personal data in the personal archive is addressed through discussing engagement and challenges. The chapter summarizes by addressing the future possibilities of researching the topic, by adhering to behavioral economics.

3. THEORETICAL LENS: BEHAVIORAL ECONOMICS

3.1 Introduction to behavioral economics in IS

The introduction to behavioral economics in the context of information system (IS) and in the concept of experiential computing provides a theoretical lens to discuss the relationship between the user, technology and everyday experiences. Behavioral economics is incorporated here as a complementary perspective to the previous chapter, which provides a theoretical background of the existing literature related to self-tracking. The previous chapter indicated, among other conclusions, that the current literature is technology-centric because it focuses on how systems are developed, implemented and used. Furthermore, this technology-centric perspective is faced with a set of challenges in the attempt to drive self-reflection in the user. The key challenge stems from data engagement due to data abundance and data insufficiency. The data engagement calls further attention to the role of the user, since it is the user that engages with the systems. However, the previous literature focuses on how to design self-tracking devices to collect the user's immediate reactions, rather than proceeding into a deeper exploration of the user's perception of these reactions. Also, in the background, this research departs from a focus on the relationship between the user and the technology and the experience that lies between the two. Therefore, this research argues that the perspective of the technology with its related challenges is to be complemented with a user-centric perspective and its specific challenges.

The field of behavioral economics over past decades has established a valid and formative presence through a substantial literature base and has been recognized by the academic community with prestigious awards, most notably the Nobel Prize in Economics in 2002. Behavioral economics have been applied in various academic fields, as well as in IS. Recently, a call for the integration of behavioral economics into IS was encouraged by Goes (2013), who believes it brings insight into the wealth of research being done on decision-making, as well as the influence of information richness within IS environments. Beyond this, there are also several studies incorporating elements related to behavioral economics in an IS research context, such as topics on the implementation of information systems,

mobile usage, information sharing, and gaming behaviors. For example, Tan & Benbasat (1990) use the concept of anchoring to discuss how users react to interfaces. In terms of mobile services, Blechar, Constantiou, & Damsgaard (2006) study heuristics, such as mental accounting, in relation to mobile service acceptance. Another example is Constantiou, Lehrer, & Hess (2014), who discuss heuristics such as affect, availability, representativeness, and status quo in a specific framework when exploring ideas regarding the usage of location-based services. Additional research is Kim & Kankanhalli (2009), who study user resistance by incorporating status quo bias to understand human decision-making. Further, Rafaeli & Raban (2003) discuss and confirm the presence of the endowment effect - ascribing value to an item simply due to ownership - when studying user patterns of sharing information and evaluating information. Constantiou, Legarth, & Olsen (2012) investigate massive multiplayer online games in relation to trading currencies and apply the dual system to discuss user intentions. These studies are examples that illustrate how concepts stemming from behavioral economics can contribute to IS by offering a new perspective that looks closer at how the user's decision-making and behavior is context-dependent and based on heuristics.

This chapter begins by describing central concepts of behavioral economics. After establishing a general understanding of the theoretical lens, the application of behavioral economics is further explained by highlighting which perspectives are used to further the discussion on self-tracking activities and related challenges. This is the dual systems theory and a number of key theoretical concepts involve both heuristics and cognitive bias: loss aversion, status quo bias, anchoring, availability, and social conditioning. These theoretical concepts are applied in a self-tracking context.

3.2 Foundational concepts of behavioral economics

Behavioral economics studies the individual's decision-making process and behavior. A central tenet is the role of the individual, indicating that it is appropriate to place the user at the center of scrutiny in the chosen research context. The perspective assumes that the individual's decisions are neither predetermined nor necessarily optimal, but are based on the information that the individual is able to compute and process (Tversky & Kahneman, 1974). The

environment that the individual resides in offers information to the user, but due to restrictions in computational capacities, it is not always possible for the user to take in all of the information (Simon, 1955). This dissertation adopts this as its departure point; it is relevant to consider when discussing the user's perception and experiences of self-tracking in everyday activities because it offers an understanding of how the user processes information, specifically personal data. Thus, a focus is placed on the individual's decisions in an everyday yet complex environment, which is made up of available cues and the framing of a context (Kahneman, Ilana, & Schkade, 1999; Tversky & Kahneman, 1974). This focus is opposed to one that assumes the individual is continuously making the optimal choice. Nevertheless, the individual might aspire to have the will to do the right thing, yet individuals are not always able to compute all environmental cues and can fall short of arriving at the optimal solution. This assumes an emphasis of cognition and argues that individuals have restrictions in information processing and "limited capacity for controlled, deliberate or systematic thinking" (Samson & Voyer, 2012, p.59). Therefore, the individual's decision may come across as irrational to others, whereas it will seem entirely rational to the self. These circumstances argue that the individual has a bounded rationality that affects the decision-making process as well as the behavior (Kahneman, 2003b). This dissertation adopts a behavioral economics perspective to be able to discuss the above issues, many of those stemming from a bounded rationality. It acknowledges and addresses the user's susceptibility to limitations in decision-making and behavior when approaching the topic of self-tracking in the context of experiential computing.

The behavioral economics perspective is distinguished from standard economics or neoclassical economics. Neoclassical economic theory departs from the assumption that agents or groups are rational, and act accordingly (Becker & Murphy, 1988; Becker, 1976). This perspective expects the agent to have stable preferences (Simon, 1955) and the capacity to conduct a cost-benefit analysis by deliberating and considering all factors in a situation (Becker & Murphy, 1988). This presupposes that the agent has access to all the relevant information and options, and thus the preconditions to compute the most beneficial outcome. It also means that the agent has the capacity to evaluate and rank options based on all of the information to arrive at the most beneficial outcome, namely maximizing utility. However, behavioral economics does not accept this premise because it

does not believe that agents are able to evaluate all of the information surrounding the user, even though it is available. Instead, the user is only able to process some of the information due to bounded rationality (Kahneman, 2003b; Simon, 1955). Behavioral economics is thus a counter perspective to standard economics, where additional perspectives, such as psychology, are invited to factor in the irrational, impulsive and unpredictable human nature into economic theory (Kahneman, 2003b; Sunstein, 2013).

Thus, the intricacies of (ir)rationality are present in behavioral economics because the user is understood to have a bounded rationality (Kahneman, 2003b; Simon, 1955). The concept of bounded rationality suggests that the individual makes decisions that are limited by information, knowledge, time or cognitive processes. The limitations arise when the individual is not able to process or compute all the information available in the surrounding environment. In turn, this individual carries his or her own limitation into the process of making the optimal decision (Kahneman, 2003a; Simon, 1955). The individual then makes decisions based only on the information that he or she can process, even though there is more information available. In other words, the individual makes limited use of the extant information because the environment is too complex to fully grasp. The approach stems from the work of Simon (1955; 1982), who reunified economics and psychology to propose that decision-makers are not necessarily rational, as asserted in neoclassical economics (Weintraub, 2007), and put forward a model that was focused on 'satisficing' instead. "Satisficing" means a combination between satisfying and sufficing, which roughly refers to a "good enough" attitude that individuals can adopt.

Inspired by Simon, Kahneman and Tversky (1972; 1974; 1992) set out to explore bounded rationality by investigating individual beliefs versus individual choice. This exploration evolved over a period of thirty years and they are now recognized as pioneers of behavioral economics. Kahneman and Tversky depart from a cognitive psychological perspective that is usually compared to economical models in research on individual decision-making. The literature points to the evidence that the individual is prone to make decisions deemed as adequate, but not necessarily optimal. The complexities of bounded rationality are also incorporated and investigated in prospect theory, a theory originating from the early works of the behavioral economics field (Kahneman & Tversky, 1979), and

serves as an alternative to neoclassical economic thought. It focuses on the individual's actual decisions rather than optimal decisions, by acknowledging the influence of individual experiences (Camerer, 1999).

The user evaluates how to pursue decision-making according to his or her computing capacities and information, yet the decisions made may seem irrational to others, even though they are perfectly comprehensive to the user. Individuals continue to behave in irrational ways that do not maximize utility, by acts such as procrastination, brawling with friends, and unhealthy eating habits (Ariely & Wertenbroch, 2002). In the same way, people currently and continuously make forecasting errors as “they predict that activities or products will have certain beneficial or adverse effects on their own well-being, but those predictions turn out to be wrong” (Sunstein, 2013, p.4). This in turn might lead to behavioral market failures that might eventually justify the incorporation of reprimands from the government sector. Accordingly, behavioral economics focuses on the underlying forces that drive individual behavior, such as whether social or economic factors influence the individual. In other words, there is a distinction between what the individual does, rather than says he or she will do (Kahneman et al., 1999; Kahneman & Ritov, 1994). This is relevant and interesting for the investigation of self-tracking because it encapsulates both performance and perception of a lived experience.

In summary, behavioral economics focuses on the user and suggests that he or she has bounded rationality and this affects the cognitive process and computing capabilities, thereby affecting the ability to make optimal decisions. The user does not have any predefined preferences but is influenced by the environment, yet the user is not able to process all of it due limitations in his or her inherent computing abilities. Moreover, the environment also influences the user's dual system of cognitive processes. This dual system includes System 1, where the intuitive, impressionable and automatic thoughts often lead the decision-making process away from System 2, an approach that involves a more controlled and structured process. The presence of the dual system is applied to this research context as a departure point to continue discussing the relationship between the user and technology and the experience between them, focusing on the cognitive processes and the behavior of the user. This perspective places emphasis on the user's cognitive challenges, whereas the previous chapter identified the challenges for

the technology. The lens allows the user's experience to be placed at the center. By presenting the visibility of the technology's challenges in relation to the user's challenges, it also provides a richer framework that is increasingly accommodating discussion of the dynamics in-between. The next step is an examination of the dual system in relation to self-tracking by separately discussing the features of System 1 and System 2 in depth. The distinguished yet related systems are both addressed in relation to the desire to make sense of the personal data.

This section served as an introduction to give a general understanding of the core concepts of behavioral economics. The next section proceeds to look closer at a central concept that is applied in this research setting, namely the dual system.

3.3 The dual system: system 1 and system 2

Since individuals have bounded rationality, behavioral economics asserts that they also operate according to a dual systems model (also called the two systems view), which suggests that the user has two cognitive systems of reasoning (Evans & Frankish; Kahneman, 2011; Samson & Voyer, 2012). The dual systems approach assumes that the individual's cognition involves two distinct modes of thinking: intuition and reasoning, also known as System 1 and System 2. This duality emerges from the field of psychology, where a dual process theory accounts for how something can occur in alternative ways (Evans, 2003). Ashraf, Camerer, & Loewenstein (2005) propose that the current application of this psychological perspective is pre-dated by Adam Smith (1759) who developed the economic theory described in his book *The Theory of Moral Sentiments*. Smith proposes that individuals are struggling between passion (an emotional state) and being the impartial spectator (the objective state). In more contemporary terms, the systems have been studied extensively by several academics (e.g., Chaiken & Trope, 1999; Epstein, 1994; Hammond, 2000; Myers, 2002).

The dual system proposes that the individual operates according to two cognitive systems: System 1 which is intuitive, emotional, swift and effortless as opposed to System 2, which is rational, deliberate, slow and effortful (Kahneman, 2003b). Kahneman (2003b) summarizes the tendencies between the two systems when he writes that the "judgments that people express, the actions they take, and the mistakes they commit depend on the monitoring and corrective functions of

System 2, as well as on the impressions and tendencies generated by System 1” (p. 1467). This means that the System 1 is mainly a reactive unit, and therefore deals with a quicker perception, whereas System 2 is slower and processes the impressions before making a decision on how to respond to the initial reaction.

System 1	System 2
Unconscious	Conscious
Automatic	Controlled
Implicit	Explicit
Effortless	Effortful
Associative	Rule-governed
Low effort	High effort
Emotional	Neutral

Table 2. Characteristics of System 1 and System 2 (Kahneman, 2003a)

System 1 is basic, evolutionary, automatic and operated by emotions. It operates largely on impressions and is thus often fast, automatic, effortless and associative. As it reacts intuitively, System 1 operates in the background that leads it to make quick decisions with ease. System 1 is “a doer, not a planner” (Sunstein, 2012). On the other hand, System 2 is slow, controlled, effortful, neutral and more flexible than System 1, which often relies on instant associations that are available to it, also known as the availability heuristic (Tversky and Kahneman, 1974; Kahneman 2003b). System 2 is intentional, controlled and often more effortful, which makes it disruptive to intuition as it attempts to make judgments based on complex thought processes. However, regardless of the more effortful process of the cognitive System 2, the intuitive and emotional nature of System 1 maybe what determines the final decision made. The characteristics of the two systems are relevant to discuss in relation to self-tracking, for they bring a stronger understanding of different reactions users might have when exposed to data. For example, System 1 is linked to the immediate reactions to the initial experience of a tracked event, or to the reactions after exposure to personal data. On the other

hand, it is possible to examine whether and when System 2 is activated in relation to experience and exposure to personal data.

To further study the dual systems, heuristics and cognitive bias are necessary concepts to present. Both heuristics and cognitive bias are related primarily to the intuitive thinking of System 1. A heuristic is a mental shortcut adopted by individuals confronted by the event of a decision, and it is an important component in discussing behavioral economics. It is a shortcut that helps individuals to quickly make sense of the complex environment. Heuristics derive from the field of psychology, although much of the relevant work was developed by Tversky and Kahneman (1974). Heuristics proposes that decisions are made based on mental shortcuts, because “people are not accustomed to thinking hard, and are often content to trust a plausible judgment that quickly comes to mind” (Kahneman, 2003b, p.1450). Instead, an individual trusts the “heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations” (Tversky and Kahneman, 1974, p.1124) which may lead to severe and systematic errors (Kahneman & Tversky, 1972, 1973; Tversky & Kahneman, 1974). Heuristics may thus sometimes lead to an incorrect judgment, and thus a cognitive bias which is then considered to be a systematic error in thinking (Ariely & Norton, 2008).

In the context of this research, the individual is exposed to the personal data in a quantified form, which may stimulate the cognitive processes related to the dual system. Numbers and dealing with numbers, sometimes called computational thinking, is commonly related to cognitive thought processes that require more effort and control, such as those in System 2 (Kahneman, 2003b). This is relevant and interesting to this research project since the self-tracking user is both collecting and exposed to personal data through mobile interfaces. The exposure to personal data is meant to invoke awareness, reflection and action (I. Li et al., 2010). Commonly, the self-tracking system design attempts to analyze the data to the user so that minimal computational effort is needed. The individual effort is required as soon as the data is to be reinterpreted by the user, even though some level of interpretation has already occurred through the IT artifact’s system. At the moment of such exposure, the fast-paced and spontaneous System 1 might circumvent complex computation and the individual could make a fast decision, or in System 2 the individual might engage in a longer and more controlled thought

process that evaluates the visualized data. For instance, the individual might associate a personal result in the tool interface with a previous result and react accordingly. More specifically, the individual reviews the step-activity-data at midday and sees that less than 1/3 of the daily goal has been recorded. Based on System 1, the individual might react that this is the customary result and then proceed as usual, whereas based on System 2, the individual might insist on considering the pros and cons of this result, and conclude that an extra walk should be included in the lunch routine. Regardless of the outcome of such a scenario, this research project adopts this approach as a departure point for the upcoming discussion using empirical data.

The application of the dual system in an experiential computing context is valuable to consider because the personal data might be regarded as a simplification but also as a cognitive overload, according to the challenges that were identified in the previous chapter. Therefore, there is an indication the dual system can enhance understanding of how different cognitive processes may be at play when evaluating personal data. This is the departure point for the rest of the chapter, which discusses the possibilities and challenges of the dual system when positioned in front of personal data.

The next section proceeds to discuss the controlled and deliberate System 2 in relation to self-tracking activities, followed by the intuitive and effortless System 1.

3.4 Conscious, controlled, and computational cognitive process

The controlled part of the individual's cognitive processes is operated by System 2 and it suggests that the user is capable of engaging in effortful and computational tasks (Kahneman, 2003b). This section focuses on this process as it is operated by System 2, by discussing aspects of the self-tracking system and the use of a device. As illustrated in the literature in the previous chapter, much of the self-tracking technology is designed with the attempt to engage System 2, followed by the incentive of inducing self-reflection and behavioral change. This means that the technology and device design assumes that the user is able and willing to employ effortful, controlled and computational efforts when exposed to the personal data.

The self-tracking system's design often assumes that the system helps the user to participate consciously and reason rationally around the collected personal data. Several frameworks (e.g., Karapanos, 2013; Pirzadeh, He, & Stolterman, 2013; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013) present a set of stages that the user goes through, which suggest that the user is consciously and deliberately making decisions. The overall procedure is to collect data, process the data through the self-tracking system, which then organizes and exposes it to the user who is suppose to gain awareness and starts reflecting on the data, potentially followed by an effect or action. Indeed, the frameworks are designed with the aim of making the user reflect as well as making behavioral changes (e.g., Fritz, Huang, Murphy, & Zimmermann, 2014; Li, 2012; Lin, Mamykina, Lindtner, Delajoux, & Strub, 2006). The exposure to personal data is believed to assists the user in becoming more aware of a behavior that is not desirable. By becoming aware, the user, it is argued, will attempt to change it. The self-tracking devices are furthermore marketed to consumers to raise such awareness by endorsing commitment to such a device as a way to change a lifestyle (Fritz et al., 2014). These may thus be referred to as commitment devices.

A commitment device is meant to serve as a device that helps the user overcome irrational behavior and act more deliberately and consciously (Ariely & Wertenbroch, 2002). It is a preventative measure that restrains users so that they "commit to making a should choice in the present rather than a want choice in the future" (Milkman, Rogers, & Bazerman, 2008, p.333). This suggests that the user is likely to want to surrender to urges in the present instead of investing for the future, but the device should aid and remind the user to do what is rationally the more suitable choice. A common example would be that the user might want to eat a whole bar of chocolate, but a commitment device reminds the user of what should be done, which is to stick to a healthy diet. The optimal choice is to do what should be done and not what is simply wanted. As an illustration of this "want versus should" contrast that the user experiences, Wertenbroch (1998) conducted a study in a supermarket regarding the purchase of foods seen as treats versus healthier foods. The study showed that "vice foods" in supermarkets more often have discounts and small packages than "virtue foods" because people are ready to pay more for smaller packages to avoid having large quantities at home, which will continue to tempt impulsive "want" self. The smaller packages can be

considered to be a type of commitment device, as it circumvents the “want” self – and therefore, shoppers are willing to pay more for such a commitment device. This example informs the departure point that the individual experiences an inherent “want” versus “should” tension as part of the self, but the device helps the user make the more rational choice (Milkman et al., 2008). The commitment device in a self-tracking context is “helpful tool to expose personal data” and therefore is “a prompting tool for pursuing self-awareness” (Sjöklint, Constantiou, & Trier, 2015, p.7).

In this research context, the self-tracking device can be understood as a type of commitment device that helps the user to perform more should-actions than want-actions with the help of technology. This is because the commitment device helps the individual’s “deliberative should selves overcome the impulsive desires of their want selves” so that “people may be able to increase their own happiness by seeking out and using commitment devices” (Milkman et al., 2008, p.334). If the user chooses to adopt a self-tracking tool, e.g., Jawbone Up, the initiation process starts with a preliminary goal (Bentley et al., 2013; E. K. Choe et al., 2014; Consolvo, Klasnja, McDonald, & Landay, 2009). The goal can be self-selected or suggested by the device. The Jawbone UP device is then worn as a wristband around the clock while it accumulates experiential data such as steps and sleep activity. Upon acquiring the device, the user may set a goal of walking 8000 steps per day. The user can review the progress of the step count throughout the day. If the step count has not been met, the user is reminded that he or she should take a walk around the block, instead of spending another hour in front of the TV. Therefore, the self-tracking device can act as a commitment device that encourages should behavior over want behavior.

As exhibited in the previous chapter, existing perspectives on self-tracking systems and the commitment device assume that the individual is able and willing to engage the controlled and effortful System 2 (I. Li, Dey, et al., 2012; Milkman et al., 2008) when exposed to personal data. The self-tracking system is assumed to be designed to stimulate the user to be more deliberate in cognitive processes and thus gain self-reflection through the data and act appropriately according to it (O’Donoghue & Rabin, 2003). Similarly, the commitment device is assumed to urge commitment to the activity onto the user so that he or she is less impulsive and more deliberate (Milkman et al., 2008). The perspective of System 2 allows a

further exploration of the dynamics between the user's application of impulsive or deliberate behavior in a self-tracking context.

On the other hand, the main challenge identified in the previous chapter assumes that the user is not adequately engaged and activated in a self-tracking context, and that this must be improved. There is thus a conflict between the type s of influence a self-tracking system has on the user. By adopting the dual system, it is possible to discuss System 2 as the dominant perspective in the literature, but also proceed to discuss System 1 as a plausible perspective in the user's reasoning process. Thus, the dual system offers a possibility to explore the complexity of the user's cognitive processes by offering two perspectives through two systems of reasoning. In other words, if System 2 is active, then the user is engaging with the data through conscious and computational activity. The self-tracking device as a commitment device also suggests that System 2 becomes engaged after exposure to data, which means the user would apply effortful thinking to explore the abundance of data for self-reflection, work with the insufficient data to gather results for self-reflection, and attempt to understand this data during engagement. However, it is also known that mental effort is limited and the engagement in effortful processes can be disruptive to the user (Kahneman, 2003a). In this research context, this limitation of the user might result in avoidance of data analysis for reasons currently undetermined. Thus, the nature of the challenges should be discussed in relation to System 1 as well, because it might be that System 1 is more often activated than System 2 after data exposure, despite the fact that it is perceived as a commitment device.

The next section proceeds to look closer at the more immediate and impulsive System 1 and how it influences the user's ability to engage in self-reflection and behavioral change after being exposed to personal data.

3.5 Intuitive, immediate and irrational cognitive process

The intuitive and reactive part of the individual's cognitive process is operated by System 1 and suggests that the user is able to react swiftly and with little effort, often overriding System 2. This section focuses on the various aspects of this inherently unpredictable system and the benefits and shortcomings of it. By engaging in self-tracking, the user is available to the exposure of personal data as a

continuous stream throughout his or her everyday life, which could instigate unexpected reactions, since System 2 is often too effortful to engage. Thus, the perspective of System 1 allows further exploration of what occurs when the user does not behave according to the intentions of the self-tracking system, which is intended to aid the user towards self-reflection and behavioral change(e.g., Consolvo et al., 2009; Li, Dey, & Forlizzi, 2011).

The nature of the identified challenges of self-tracking systems and devices indicate that the user turns to the intuitive and swift reactions of System 1 after exposure to personal data. This is contrary to the assumptions of several self-tracking system frameworks previously presented (e.g., Karapanos, 2013; Li et al., 2010; Pirzadeh et al., 2013; Verbert et al., 2013). These assume that the user is rational and thus behaves in a deliberate fashion. However, despite the anticipation of the user to think and behave in a deliberate way, the challenge is to keep the user engaged with the data in that manner. The lack of engagement may result in little or no reflection, which in turn suggests that System 1 offers a reaction and prevents further reflection within System 2.

Therefore, the user does not behave as the system design anticipated, leading to failure to become self-reflective on the basis of the system's intentions. For example, when the user is exposed to an abundance of data, the user has issues with interpreting and making sense of the data, and therefore leaves it without arriving at expected insights, which leads to little or no self-reflection and the absence of behavioral change.

The introduction of the dual system theory opens a possibility for discussion beyond attributing the user with deliberate reasoning and behavior and hopefully come closer to understanding alternative scenarios. The incorporation of this theoretical lens might shed light on the limitations on the user and how these affect the reaction and reasoning around personal data collection through self-tracking activities within the context of experiential computing. This section presents relevant theoretical concepts related to System 1 to continue this exploration.

Theoretical concept	Definition of concept	Self-tracking perspective
Loss aversion (Kahneman & Tversky, 1991)	The individual has difficulty in changing the current status quo (REF) because losses loom larger than gains (REF).	The user feels uncomfortable when achieving less than the preset goal because this is perceived as a failure.
Status quo bias (Kahneman, Knetsch, & Thaler, 1990)	The individual attempts to maintain the current state.	The user tries to maintain the current state by reaching the daily goal placed by the self-tracking system.
Anchoring (Tversky and Kahneman, 1974)	The individual attaches value on the first piece of numerical information given, which serves as an anchor for future decisions.	The user is anchored to the original preset goal (e.g., step or sleep) that is entered by the self-tracking system.
Availability (Tversky & Kahneman, 1973)	The individual relies on the latest piece of information that comes to mind to make a judgment.	The user relies on the latest memory that relates to the data, rather than relying on the data.
Social influence (Cialdini, 2008)	The individual is affected by the presence and participation of other individuals in the same activity.	The user tries to match personal performance data with the network's data.

Table 3. Definitions of theoretical concepts and application to self-tracking

The chosen relevant theoretical concepts related to how an individual may perceive his or her own numbers are presented below. The section start with one of the most central concepts in behavioral economics: loss aversion. Loss aversion is a part of prospect theory, as mentioned earlier (Kahneman and Tversky, 1979). Loss aversion has ever since inspired a range of research, which has resulted in concepts such as status quo bias (e.g., Kahneman, Knetsch, & Thaler, 1991; Thaler, 1980). Another central concept in this category is anchoring (e.g., Ariely et al., 2006), and availability (Tversky & Kahneman, 1973).

The concepts are considered from the perspective of personal data that is collected in a self-tracking context, rather than in terms of general data. However, the user may be exposed to factors that influence the perception of his or her data and therefore does not make choices in isolation but instead, the choices are “shaped by—and embedded in—social environments” (Loewenstein in Samson, 2014, p.7). Therefore, the theoretical concepts mainly focus on the exposure of the personal data and acknowledge that influences can be driven externally, e.g., by social environments. The concepts are elaborated in the next section.

3.5.1 Loss aversion and status quo bias

This first section on perception of personal numbers presents loss aversion and status quo bias. These concepts aid in understanding fear of loss and discussing the value and subsequent complications that might be related to using a self-tracking device for seeing personal data.

The concept of loss aversion underlines the individual's perception that the experience of loss appears greater than the gain (Kahneman et al., 1991). The reluctance to part with the object is not to “enhance the appeal of the good one owns, only the pain of giving it up” (ibid, p. 197). As a result, individuals prefer to stay clear of risk to avoid any potential danger of loss. Due to a possibility of experiencing loss, it is common for individuals to attempt to maintain the current state (i.e., avoid losses or failure), also known as the status quo bias (Kahneman, Knetsch, & Thaler, 1990; Kahneman et al., 1991). The fear of loss leads individuals to be reluctant to change and prefer options that do not cause change, and such “uncertainty itself can lead people to status quo inertia” (Hong, Thong, Chasalow, & Dhillon, 2011, p.241). However, a status quo bias is not necessarily static but may change if the individual experiences a heightened value from an alternative. For example, a study showed that the user of an experiential device, such as a smartphone, would revert to location-based services over more traditional options, like maps, because the location-based services gained a heightened value due to convenience (Constantiou et al., 2014). Another study, showed that the status quo is preferred because the “uncertainty associated with the changes can lead people to prefer no change and no action” and “emphasize the importance of examining users’ reactions to frequent changes with IS” (Hong, Thong, Chasalow, & Dhillon, 2011, p.241).

Loss aversion and status quo bias have also been applied to an IS context. For example, loss aversion was explored alongside the status quo bias (Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988). The study discussed user resistance to IS implementation and showed that the perceived value of costs, such as effort, disrupted the user's acceptance of the technology. These findings are interesting because they fuel the understanding of how individuals are motivated

to continue engaging in a behavior and even develop habits on the basis of this behavior.

Loss aversion can be applied in several ways in a self-tracking context. For example, loss aversion might be understood as occurring if the user fears not reaching the preset goal because of the related pain that comes with such failure. The inability to reach a preset goal is thus a loss that is considered a failure, as opposed to an equivalent gain from surpassing the goal. The user may also be confronted with challenges of data engagement, such as abundant or insufficient data. In one example, the concept of loss aversion assumes that the user does not want to part with the data accumulated even though he or she is unable to process and organize it because of its abundance. The data stays as storage, much like Bell and Gemmell's (2007) digital personal archive, rather than becoming an active consulting source for success and failure in relation to the preset goal. The engagement with the data is then decreased, but the user is still adamant about continuing to collect data out of a fear of losing this possible consulting source. As an example of data insufficiency, the user does not have enough data but still cannot discard the collected data because this causes a similar discomfort. The engagement with the data is also decreased because there is not enough to be relevant or useful so the user does not interact with it.

At the same time, as soon as the user starts to self-track, the user seeks to achieve a status quo. In an application for this research context, the assumption is that the status quo entails staying balanced with the daily preset goal, rather than underachieving, or even overachieving. For example, the user has a goal of 10,000 steps per day and aspires to reach this every day and moderates behavior accordingly. The application of the status quo concepts also assumes that the user is likely not to do more steps than necessary (i.e., overachieving) but is content as long as he or she reaches the preset goal. In reference to the challenges of data abundance and insufficiency, the user might then just focus on keeping a status quo, rather than actively evaluating the existing data and changing behavior accordingly and appropriately. In this manner, the user decreases data engagement for the purposes of maintaining a status quo.

3.5.2 Anchoring

Anchoring is a cognitive bias that is unconsciously employed by individuals in uncertain events, causing bias toward an initial value when different values are presented. This suggests that individuals often have little idea of how to value things and experiences (Frederick, Kahneman, & Mochon, 2010; Tversky & Kahneman, 1974). Instead, the individual has a tendency to attach preference for a particular piece of information when making decisions, namely the first piece of information received. This is common in situations where individuals are dealing with new concepts, where no reference point is present. Anchoring is common in situations that involve numerical predictions (Tversky and Kahneman, 1974), making it especially relevant in an experiential computing context where numerical visualizations in the tools are common.

A random number may thus act as a reference point for individual decision-making (Ariely, Loewenstein, & Prelec, 2006). As an example, a set of invited participants were asked to write down the two last numbers of their social security number on their participation form. They were then shown a number of different products, like wine. The students were asked if they were willing to buy the products for a price equivalent to the two last digits of the social security number. The study found that “Although students were reminded that the social security number is a random quantity conveying no information, those who happened to have high social security numbers were willing to pay much more for the products”(ibid, p.3). This means that a random number can indeed have an impact on an unrelated item in an unrelated context.

In the context of IS, anchoring has been applied in a number of studies. Alrushiedat and Olfman (2013) find that discussion forums that feature anchored elements, such as visual markings (e.g., highlighted text), are more successful in terms of participation and engagement because these markings provide cues of attention, namely a heuristic. The authors thus argued that anchoring is “a process of creating reference points” that “help prevent drifting away from the context” which leads to more elaborate discussion threads (ibid, p.135). Venkatesh (2000) also explored determinants of perceived ease of use and found that control, intrinsic motivation and emotion “serve as anchors that users employ in forming perceived ease of use about a new system”(p.355). Moreover, Allen and Parsons,(2010) found that anchoring when writing code could lead to erroneous

bias as participants would reuse rather than rewrite code. This showed that the initial anchor, i.e., the original code, instigated overconfidence that resulted in insufficient results.

In relation to this research's primary interest, anchoring assumes that the individual is influenced by the first piece of numerical information received, such as the preset self-tracking goal. The preset goal functions as an anchor, because the user does not have any other point of reference to evaluate the data collection on steps and sleep. The anchor is then the basis for whether the user deems the data collection satisfactory or not.

With respect to the challenge of data engagement, the concept of anchoring might entail a decrease in data engagement. As mentioned, the user rests on the anchor as a numerical reference point for what can be considered to be success or failure for steps and sleep. During the experience of data abundance, the anchor is thus consulted quickly to deem success or failure, implying that any deeper reflective process by System 2 is abandoned, and so is, then, any further engagement. A data insufficiency also suggests that the user does not move into any deeper process, but instead chooses to consult the anchor for evaluation of the lack of data. Thus, in the same manner, the engagement is decreased.

3.5.3 Availability

Individuals make judgments under uncertainty (Tversky & Kahneman, 1974), which is illustrated in the availability heuristic. The availability heuristic suggests that the individual grabs the information that is easily available, rather than assessing the full picture (Tversky & Kahneman, 1973). For instance, a person might assess the likelihood of middle-aged men getting heart attacks based on such occurrences in the family and friendship history. Another example is that an individual will judge the probability of snow in November by considering the last most similar event, for example, last year's November (Kahneman & Tversky, 1972, p.451). These examples are illustrations that individuals have a natural tendency to think in terms of personal stories as examples and assume that the more stories that verify a statement, the more likely that the statement is true. Moreover, individuals think that if a story can be re-called, then it must be important. Stories that are not remembered are deemed irrelevant. Therefore, the

availability heuristic assumes that the individual responds to ease of retrieval, and reverts to the most accessible piece of information to make a judgment. Essentially, individuals use past events to judge future events. This heuristic is intertwined in cause and effect (Nisbett & Wilson, 1977, p.251). Availability is more likely to occur when the object or event is distinguished by incident (Kahneman & Tversky, 1972). In this sense, availability focuses on denotation.

The application of availability in a self-tracking research context assumes that the user might use the latest piece of information readily available to compare to the personal data. Availability is similar to anchoring, but focuses more on qualitative data rather than numerical data. However, by relying on the latest perception of the experience, the user might encounter confirmatory or contradictory account of the lived and perceived experience. For example, the user usually hates waking up at 6 a.m. However, the user's perception is that in the summer months, the user is not bothered by waking up at 6 a.m. The user discards the exposure to the sleep data recording less sleep in the mobile app interface, and rests on the perception and experience that the summer months require less sleep even though it might be more likely that the brighter mornings have an impact on the wake up routine. Due to the user's perception of the experience, the user trusts the information available in his or her mind, rather than that offered by the tracking device. This might lead to dismissing the accuracy of both the data and the device. The availability heuristic presents the assumption that the individual trusts the latest information of the lived experience.

The challenge of data engagement might also invoke availability. In terms of data abundance, the user might rely on one or several memories of recent step activity, rather than consulting the data of the activity because there is too much data. For example, the user has the perception that he or she has had a stressful day with lots of errands, which usually means a lot of walking between different places. The user rests on the memory of the last time he or she had a similar day of errands, and assumes that the data will be similar. This also means that the user does not feel a need to consult the data, and engagement is absent. In terms of data insufficiency, the user relies on one or several memories of activity instead of consulting the available data, because there is not enough data to become informed about the activity. The engagement with the data is also likely to be absent, and may decrease over time.

3.5.4 Social influence

Behavioral economics assumes that performance is affected in a social environment. Individuals become stressed when prompted to perform under social conditions, such as giving a presentation in front of a group of colleagues. A lab study investigated whether participants would comply with safety regulations based on social pressure (Wogalter, Allison, & McKenna, 1989). The study assumed that individuals are “more likely to comply when other persons comply” and that “people are less likely to comply when others do not comply” (p.136). Merely the presence of another person who exhibits compliance had an influence on the participants in the study, whereas the compliance was lower when the other person failed. Social influence may then be seen as a normative influence that individuals strive towards to be accepted (Aaronson, Wilson, & Akert, 1994). Studies also show that social pressures might impede performance, particularly when performing next to successful individuals. One study showed that the presence and participation of Tiger Woods at a professional golf tournament affects the other players for the worse. The effect was even greater on higher-skilled players than lower-skilled players (Brown, 2011). Should the same argument be applied to a self-tracking platform, then there is a possibility that performance is impaired if individuals are constantly exposed to high performing individuals in the social network.

Moreover, individual “preferences are not simply a matter of basic tastes; they are also influenced by norms” (Samson, 2014, p.7). Social norms that arise from the environment influence what individuals consider appropriate behavior by looking at what the majority is doing (Ariely, 2008; Banerjee, 1992). Moreover, the influence of social norms is related to the individual’s desire to keep a positive view of the self and to keep it consistent and continuous (Cialdini, 2008). When this desire is threatened, individuals are willing to change their attitude or behavior (Samson, 2014). For example, a study about fundraising showed that potential donors contributed more when they were given ‘social information’ about the contributions of others (Shang & Croson, 2009).

Several self-tracking tools include social elements, such as inviting other users to participate in sharing performance data, and also in viewing and commenting on

each other's self-tracking practices. The concept of social influence assumes that the presence of other individual's engaging in the same activity as well as the exposure to other's results is likely to influence not only the individual participant's performance but also cognitive processes. The self-tracking user is likely to be influenced by other users. In the event that the friend is performing well, the user is likely to strive towards similar results of data collection. However, if the friend is substantially out-performing the user, the user might perform worse than usual. For example, if a user sees that a friend has walked 8500 steps, the user might attempt to match this. On the other hand, if the friend has walked 24 000 steps, the user might not muster the strength to try to reach this goal and loses interest in the activity.

In relation to the main challenge of data engagement, the role of social influence may be relevant in relation to both data abundance and data insufficiency. For example, when the user is exposed to an abundance of data, there is a possibility that the user does not analyze the data in its isolation, but turns to the social network for comparison. On the other hand, data insufficiency might spark a similar reaction where the lack of information spurs the user to turn to the social network data to compare their own data. These scenarios fuel an engagement from the user that involves the social network in the development of the perception of the experience of being exposed to personal data. The involvement of the social network automatically entails some type of data engagement, but there is a possibility that the user neglects his or her own data in favor of reviewing others' data.

Thus, the perspective of social influence assumes that the self-tracking user is influenced by the external environment when being exposed to and reviewing the personal data.

3.6 Chapter summary

This chapter presented behavioral economics and key theoretical concepts that serve as a theoretical lens to complement the understanding of self-tracking activities, with a focus on the challenge of engagement. First, a general introduction is made to behavioral economics and the existence of the individual's dual system. The application of System 1 versus System 2 in a self-tracking

context is then developed, particularly by presenting a set of key theoretical concepts related to System 1 reactions. In particular, these consist of heuristics, a mental shortcut, and cognitive bias, a systemic error in thinking, as two departure points for discussing cognitive processes among self-tracking users. The chapter examined and revealed how self-tracking systems and related practices can be profiled in a dual system setting.

4. METHODOLOGICAL CONSIDERATIONS AND EMPIRICAL INVESTIGATION

4.1 Research approach

This section starts by presenting this research project's main philosophical foundation from an ontological and epistemological perspective, which is rooted in critical realism (e.g., Bhaskar, 1978). This is followed by the overall basis for assumptions and beliefs of this research project. Thereafter, the implications for the research design are outlined and elaborated with relation to its impact on the literature review, method, data collection and analysis.

The philosophical perspective informs the research by presenting a set of foundational assumptions that permeates as well as guides the research project as whole. This project's research design is informed and influenced by critical realism. The importance of presenting the foundational assumptions is to provide transparency of the philosophical perspective that is shaping the research design and argumentation, so that onlookers can understand and scrutinize the research. Moreover, the transparency of these considerations is also important because it explains the researcher's underlying interpretation of the world. Therefore, it is essential for me, as a researcher, to present my understanding of the world, so that my applied reasoning is clear to follow, but also to let it be open for discussion and analysis. As a researcher, I believe I am subjective because I carry my own beliefs and values. It is not possible to entirely detach or separate myself from my perspective. This means that my perspective is unavoidably imposed on my work, while a different researcher on the same topic might carry an entirely different worldview with a different research approach. Due to such a subjective predisposition, I seek to be as transparent as possible about my choices of philosophical assumptions and the research design, so that it is clear how the research is framed (Hyppänen, 2008). However, the influence of a personal predisposition on the world and how knowledge is obtained is also influenced by the research objective and context (Van de Ven, 2007). Having underlined my departure point for the importance of assuming and presenting a philosophical perspective, I must also emphasize that this is not an attempt to assert the chosen

perspective is superior, but rather to outline a discussion of the appropriate paradigm to address the chosen research question.

In information systems (IS) literature, the distinctions of philosophy often range between positivism, interpretivism/relativism, and realism (Klein, 2004), and as illustrated by the adaptation of a framework by Van de Ven (2007). The framework describes the constellation of different philosophical assumptions and how critical realism is positioned in relation to other perspectives, such as positivism and relativism. The philosophical considerations adopted in this research are understood as being primarily of an ontological and epistemological nature. The ontological perspective revolves around the existence and nature of the world and asks what is real. The epistemological perspective is the nature of the knowledge and how it is acquired by asking what is true. Epistemology is thus about the relationship between the reality and the researcher but also the methodology used by the researcher to explore this reality. Then, the methodology is the perspective that seeks to understand how the world of what is real can be examined. The figure bellows positions these perspectives in relation to each other and relevant paradigms considered.

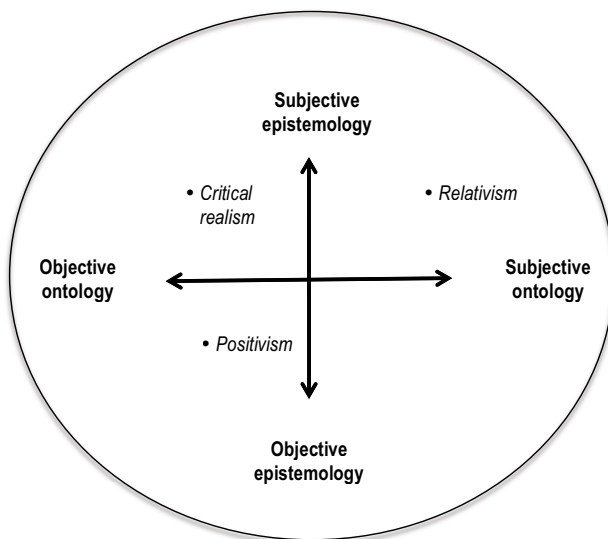


Figure 5. Overview of philosophical perspective.

A mixed method is applied in this research and it involves both a quantitative and qualitative study, yet despite the nature of these studies, they do not directly draw on a positivist versus an interpretivist perspective. Instead, critical realism offers the possibility of navigating between a subjective epistemology and an objective ontology, allowing a combination of abstractions to discuss the complexity of the underlying research interest. In contrast, positivism and interpretivism were concluded not to be suitable for the purposes of this research. Positivism asserts that data exists objectively and it is up to the researcher to collect and systemize this data (Alvesson & Sköldbberg, 2009). Points of critique are that it is too focused on theory and therefore excludes the element of discovery, neglects implicit meaning and purpose, and strips the context of valuable subjective meaning (Guba & Lincoln, 1994, p.39-40). This conflicts with the research interest, where implicit and subjective meaning is important to address when discussing the perceptions of experiences that individuals might endure during self-tracking activities. On the other hand, relativism is positioned on the opposite side of the spectrum of positivism. As an umbrella term, relativism carries a number of paradigms that counter the positivist perspective, such as interpretivism, constructivism, hermeneutics and post-modernism. It “emerged in reaction to, or in denial of, positivism” and to “view reality as socially constructed, and the goal of social science as that of understanding what meanings people give to reality, not only to determine how reality works” (Van de Ven, 2007, p.46-47). However, the paradigm does not assume an objective reality, such as evaluating the performance measures statistically, which is considered an essential part of the study investigating data collected by self-tracking tools. However, it could be helpful to discuss the implicit meaning, a way to accept that reality varies depending on values and viewpoints that are shaped through interactions with other people.

As the various philosophical perspectives were examined, I attempted to consider a perspective that acknowledged my interest as well as my predispositions, while at the same time being open to alternative options. This guiding principle is vital because the researcher “should understand and acknowledge the extent to which the perspective they adopt will focus their attention on some things and not others, and bias their perception of the phenomena they study” (Orlikowski & Baroudi, 1991, p.24). In this light, I assert that my predisposition is that there is a reality that exists but it is approached differently by each individual, who subsequently

creates a subjective meaning about it. In this sense, I do not believe that there is a completely objective and error-free truth to be understood by the individual nor that everything is entirely constructed by the individual. This perspective shares relativism's approach on the role of subjectivity, yet has a more assertive stance on what is constituted and understood as reality. Within these reflections, I understood that I am not a positivist who believes in an objective reality nor am I a relativist who asserts that reality is constructed. Instead, I was intrigued and persuaded by the critical realist view.

This research project adopts a critical realist view in accordance with the writings of Bhaskar (1978;1998), which presents a philosophical perspective that asserts that reality is independent of individual attempts to understand it, while at the same time individual knowledge about the world is determined by the way it is interpreted (Psillos, 2007; Van de Ven, 2007). Similar to the behavioral economics perspective, critical realism assumes that human knowledge of reality is fallible, because we cannot fully comprehend or observe reality. The application of this perspective has also been done in the IS field. Mingers (2002) argues that critical realism is valuable to IS because it addresses both hard and soft approaches (such as empiricist versus interpretivist paradigms). Adopting the same assumption, Wynn & Williams (2012) elaborates by explaining that critical realism research aims at finding the explanations and causes of a particular phenomenon. Therefore, it is focused on how and why an event has occurred by attempting to identify the "mechanisms that emerge from the components of a physical and social structure to produce the events of interest" (p.794). In particular, abduction (also known as retroduction) is relevant, since it focuses on identifying and elaborating on tendencies of "structure that may have interacted to generate explicated events" (ibid, p.796) and it is "the best approximation of the world" (Mingers, 2002, p.299).

Occasionally, critical realism is also referred to as transcendental realism. This research project adopts the term critical realism in a broad sense with a focus on the foundational concepts, but there are several strands and variations, such as emergent realism (Mark, Henry, & Julnes, 1998), subtle realism (Hammersley, 2002) and innocent realism (Haack, 2004). The common feature of these strands of realism is that of an objective ontology paired with a subjective epistemology (Maxwell & Mittapalli, 2010).

A foundational part of critical realism is that it is structured as three levels, or realms, of how reality can be approached and understood, and these levels are adopted by this project. This is illustrated in the table below. The three realms describe the real realm, the actual realm and the empirical realm, as adopted by Mingers and Willcox (2004).

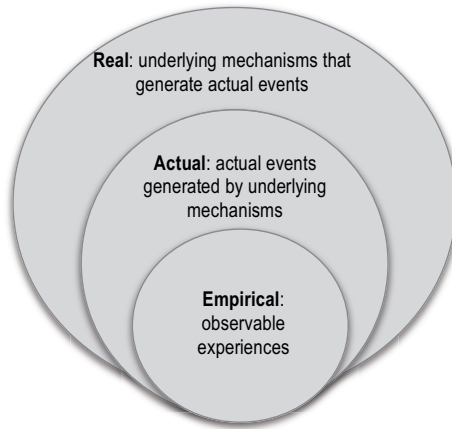


Figure 6. The three realms of critical realism.

The underlying mechanism or structures of the real realm are responsible for what can be observed. The real realm is the whole of reality; however, it cannot be seen in itself but can only be speculated upon. This speculation also assumes that there is no direct knowledge of it. As individuals, the understanding of what is real is limited due to our subjective outlook and experience. Thus, the understanding of the real realm is limited due to the individual's limitations (Mingers, Muthc, & Willcocks, 2013). For example, gravity is an underlying mechanism but not something that the individual can see.

The actual realm contains the events that are generated or not generated by the underlying mechanisms of the real realm. The actual can be observed or experienced. In relation to gravity, the observation or experience could be the apple falling from the tree.

The empirical realm refers to experiences, most notably the observable experiences of individuals. It is in the empirical realm that the researcher, as an observer of events and experiences, can make speculations about the real (Mingers et al., 2013; Mingers & Willcocks, 2004). In relation to gravity, this would be the attempt to have the experience followed by understanding why the apple falls from the tree.

In essence, the three realms underline the idea that merely because something cannot be observed, does not mean it does not exist.

By adopting a critical realist perspective, I adopt an objective ontology with a subjective epistemology. This assumes that reality exists independent of individual cognition, but the means of making sense of it is subjective (Maxwell & Mittapalli, 2010). In other words, the real world exists but because of the individual's limited understanding, it is not possible to understand it fully. Therefore, any data that is collected, such as observations, cannot hold a universal truth nor be error-free but are instead theory-laden. I maintain that this philosophical position is also suitably aligned with behavioral economics because it departs from the assumption that the individual is rationally bounded and acts upon these limitations and the information and knowledge offered by the environment (Kahneman & Tversky, 1979; Kahneman, 2003b). Any collected data is influenced by individual values and knowledge, which calls for methods that can adhere to the acknowledgement of the complex reality that demands multiple perspectives (Van de Ven, 2007, p.38).

My role as a researcher with a critical realist perspective is to observe the empirical realm and based on this, be aware that only speculation can occur about the transcending realms. According to Mingers et al. (2013), the researcher should take a phenomenon of interest, observe it in the empirical domain, and then describe it and relate it to mechanisms and events, which may be non-physical or non-observable. It is up to the researcher to make the proposals or hypotheses based on the speculations regarding the observations, yet the underlying mechanisms might still have competing proposals. Even though it is not possible to fully grasp or know reality, it is still valuable to the results to try to exclude or remove any alternatives to the proposals. The elimination of alternatives can be done by testing the effects through using multimethodologies, such as mixed-

method (John Mingers, 2001; Venkatesh, Brown, & Bala, 2013). The philosophical perspective aids the choices in methodology to conduct the mixed method approach.

The motivation of this study is to study the emerging phenomenon of self-tracking for self-quantification. The application of the three realms of critical realism is valuable in structuring how and what knowledge can be approached in this investigation. In the table below the three realms are described and contrasted against a possible scenario for self-tracking as a reflective exercise.

Realm	Levels	A self-tracking context
Real	Underlying mechanisms or structures responsible for what can be observed. These have enduring properties.	The underlying structure is the space, or the natural world, where the experience of the user occurs. For example, the setting of running through the park, such as weather, temperature, vegetation, personal performance (speed of run).
Actual	Actual events (or non-events) that have been generated by the mechanisms in the real realm.	The actual event is the lived experience that is captured by self-tracking activity. For example, this might be the actual run through the park.
Empirical	Observable experiences. The researcher, as an observer or experiencer, can only speculate about the experiences.	The observable experience is the data that is collected, presented and interpreted by the self-tracking user, such as the personal data exposed by the self-tracking device. For example, this is the data collected by the self-tracking device about the run.

Table 4. The three realms of critical realism compared to self-tracking context.

In summary, the reflections on ontological and epistemological concerns in relation to my own predispositions, concurrent with the research topic and goals, lead to several considerations that are aligned with a critical realist perspective. This research project uses a critical realist approach to investigate experiential computing with a focus on self-tracking activities and how that influences the user's perceptions on personal performance. Both perspectives foundational assumptions accept that individuals have different experiences because they inherently experience different parts of reality

4.2 Research design: A mixed method approach

The empirical investigation of this research project applies a mixed method approach which includes two studies, quantitative and qualitative, respectively. Such a methodology is relevant and encouraged by a critical realist perspective (Mingers et al., 2013; Van de Ven, 2007). Since critical realism acknowledges that there exist different types of objects of knowledge with different ontological and epistemological characteristics, different methods are both valid and even required to access them (Mingers, Mutch, & Willcocks, 2013). The methodological consideration of a critical realist perspective “validates and supports key aspects of both quantitative and qualitative approaches” (Creswell & Plano Clark, 2011, p.44). Therefore, critical realism is compatible with a mixed method approach (Creswell & Plano Clark, 2011; Maxwell & Mittapalli, 2010).

The mixed method approach has furthermore been supported by IS research “to provide rich insights into various phenomena and develop novel theoretical perspectives” (Venkatesh et al., 2013). Moreover, Mingers , (2001) argues that understanding of a social phenomenon must be done by applying multiple perspectives to capture the objective world, the subjective world and the social world. This is supported by Ågerfalk (2013), who suggests that mixed method tools and paradigms will aid in this conquest. In a rapidly changing IS context, “existing theories and findings do not sufficiently explain or offer significant insights into a phenomenon of interest” (Venkatesh, Brown, & Bala, 2013, p.24) and mixed method is a “powerful mechanism” to approach such situations and make contributions (ibid). Given the influence of the self-tracking context in IS-

related literature, a mixed method approach is relevant to explore the phenomenon.

It is important to rigorously present the research design because it guides the methodological decisions and sets the logic by which interpretations are made (Creswell & Plano Clark, 2011). This chapter provides an overview and introduction of the research design and in following chapters, this is presented in more detail. This study is characterized as a mixed method study because of the dual nature of the data collection, namely quantitative and qualitative data. A mixed method study should “include at least one quantitative method (designed to collect numbers) and one qualitative method (designed to collect words), where neither type of method is inherently linked to any particular inquiry paradigm” (Greene, Caracelli, & Graham, 1989, p.256).

The first study is a field study where new and inexperienced users are invited to begin self-tracking and it is aimed at viewing how behavior and performance develops over the first period of time spent using an experiential device. The second study is an interview study of experienced self-tracking users and is designed to gather a deeper understanding of the perceptions and reflections that evolve during engagement with self-tracking practices. The experienced user is chosen for this study because he or she has voluntarily accepted and adopted the prerequisites of the device and its paradigm without the imposition of the research project.

An outline of the two studies is presented in the table below, and then followed by an introduction to the methodological considerations regarding a mixed method.

	Study 1: New users	Study 2: Experienced users
Study type	Quantitative and qualitative	Qualitative
Pre-study	Pilot study: 13 participants	-
Research question	How do new users experience and perceive the practice of self-tracking in terms of personal performance?	How do experienced users experience and perceive the practice of self-tracking in terms of personal performance?
Method	Field study	Interview study
Scientific reasoning	Abductive	Abductive
Data	Quantitative data on performance (835 observations) Qualitative post interviews	Semi-structured interviews
Sample	University students 34 new users Total: 34	Purposive sample 42 Jawbone users 12 Fitbit users Total: 54
Gender	18M 14W	30M 24W
Analysis	Both quantitative and qualitative analysis	Qualitative analysis through thematic analysis
Software for analysis	Quantitative: SPSS Qualitative: MaxQDA	MaxQDA

Table 5. Overview of the empirical studies.

In this research project, the two studies rely on collecting various types of data for the purpose of gaining comparable perspectives on the performance and related perceptions in relation to self-tracking activities. This is advantageous to the research, as the two perspectives contribute valuable data in different ways. The quantitative aspect gives insight into the performance as well as to influences from the self-tracking activities, while the subsequent qualitative aspect allows for an elaboration and comparison to the perceptions as they are related to the performance measures. At the same time, the qualitative aspect has issues with generalizing findings to a larger group (Creswell & Plano Clark, 2011). Thus, the weaknesses and strengths of respective method moderate each other and enable making meta-inferences (Venkatesh et al., 2013). Moreover, a mixed method can be relevant in several scenarios, such as when data sources are insufficient, initial results must be explained, exploratory results need generalization, theory needs to be employed or the topic needs multiple phases of inquiry (Creswell & Plano Clark, 2011).

More specifically, the mixed method has a sequential mixed design (Tashakkori & Teddlie, 1998). The research design begins by placing the focus on the quantifiable aspects of self-tracking by conducting a field study that gathers information on the performance of users as well as the perceptions of users. This study is thus quantitative regarding performance measures (through activity tracking) and qualitative regarding the perceptions (semi-structured post-study interviews). This study provides an understanding of how the new user uses an experiential device and how it affects performance, as well as perceptions about performance. The post-interviews further shine light on how the user perceived this time with the device. In order to further explore the perceptions of the user, a second study with a qualitative approach is designed to gather deeper insight into the user's perceptions of the behavior. In this way the studies are independent of each other but complement and contrast each other as well (Creswell & Plano Clark, 2011).

The studies are interrelated—they inform each other to understand the phenomenon of interest (Venkatesh et al., 2013). To give an overview, the research design is illustrated in Figure 7. The first study is developed to help shed light on what happens when an individual adopts a self-tracking device by gathering quantitative data on behavior, such as step and sleep, and the interaction

with the IT artifact that captures, translates and presents this data. The second study then attempts to further understand this adoption by investigating the user's perception of his or her own behavior in relation to the activities.

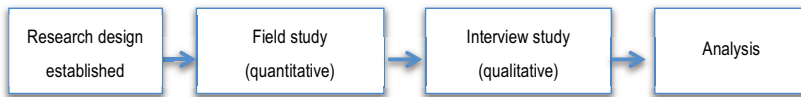


Figure 7. The mixed method process.

In this research project, abductive reasoning is used to drive the research project. Abductive reasoning has been argued to be “inference to the best explanation” (Harman, 1965; Lipton, 2004). It is also compatible with the adopted philosophical perspective of critical realism (Mingers, 2002). The application is done by “the process of generation and ranking of hypotheses in terms of plausibility, which is followed by the derivation of predication from them by means of deduction, and whose testing is done by means of induction” (Psillos, 2007, p.4). In other words, an unexplained phenomenon is addressed by making hypothetical explanations that are investigated by moving “from experiences in the empirical domain to possible structures in the real domain” (Mingers, 2002, p.300). The explanations may exhibit competing assumptions, so the analysis consists of eliminating some explanations while supporting others. Abductive reasoning requires that the researcher engage with the world and it is the means by which an inconsistency with the understanding or theory of the world is discovered (Van de Ven, 2007). Abduction is in contrast to deductive and inductive reasoning, which are more commonly applied in IS research. In contrast, inductive reasoning is the attempt to discover a new pattern or hypothesis, whereas deductive reasoning attempts to prove a pattern or hypothesis.

4.3 Overview of the empirical studies

This section gives an overview of two forthcoming studies and the context of the study, specifically, the self-tracker that is investigated. The two studies are part of an exploratory mixed method study. The aim of the research rests in the premise that self-tracking related research can benefit from further development of

understanding the user's perspective from various viewpoints, as identified in the previous chapters on theoretical background. In the case of investigating emerging phenomenon, a mixed method approach is also particularly useful and helps developing new theoretical perspectives (Venkatesh et al., 2013). The exploratory perspective in this mixed method is chosen because at the start of the project, little previous knowledge was available on the to user's perceptions; thus, it was deemed appropriate as well as desirable for study. Nevertheless, in order to fully investigate the user's perceptions, multiple perspectives on the same activity must be examined (Mingers, 2001), for the individual's understanding is limited and can therefore only convey what he or she understands. For this reason, the first study focuses on new users' performance in order to investigate performance development but also focuses on experiences and engagement in self-tracking activity. The second study is a continuation and a complementary study to the first study and aims to investigate the experienced user's perceptions of the experience of self-tracking activity.

4.3.1 Study 1: Field study with new users

The first study is a field study that takes its starting point from the interest in what happens in terms of behavior, such as step and sleep performance, when an individual adopts a self-tracking device, such as the Jawbone UP. The purpose is to observe the behavior of the new user and how performance evolves during the first time period with the device. A field study was chosen because it is a useful method to assess information that leads to a better understanding of social structure and social processes (Webster & Sell, 2007), such as attempting to better understand the self-tracking process. It can also inform further about "the quality of causal inferences in the social science" setting (Dunning, 2012, p.2).

The field study is a well-established part of the IS field (Benson, 1983; Paul & Jr, 2004; Sanders & Courtney, 1985; Walsham, 1995). It is a type of in-depth study where the collection of data is in the empirical realm, outside of a lab setting, and "in spite of having hypothesis testing as the main objective, no manipulation of independent variables is undertaken" (Krishnaswamy, Sivakumar, & Mathirajan, 2009, p.164). However, in this research context, users in everyday life are followed in order to learn even more about the behavior while using a Jawbone UP. This method is relevant for the purpose of this research interest, because it

allows observation of the new user as he or she starts to use a self-tracking device and gains an understanding of how performance and related behavior develops. This in turn is followed by an inquiry about perceptions in semi-structured interviews after the field study is completed. It should be noted that the field study method is not chosen to find generalized results, but is considered useful for identifying problems of the research context (Krishnaswamy et al., 2009). In terms of self-tracking activities, the field study may thus be valuable to gain understanding of the user's first weeks of usage and the challenges that might accompany this. The data might also help identify the issues that could be of interest for further investigation, such as the discrepancy between actual performance and perceptions related to this performance.

There are restrictions with every chosen empirical collection. When it comes to the field study, it should be clarified that it is not a single method that collects one single type of data. Zelditch (1962, p.567-568) specified three types of data, or information: incidents and histories, distributions and frequencies, and generally known rules. In this research, the field study collects primarily performance data, which consists of logging the frequencies of steps and sleep. It also collects the participant's perceptions of this step and sleep performance on dichotomous scales, that is, numerical distributions. This data consists, therefore, of enumerations or samples of the field study. Moreover, it also collects post-interviews, which is a type of as narrative, namely incidents and histories. The generally known rules are also discussed through the post-interviews, together with support of the literature from the theoretical background.

When designing this study, many considerations were explored on how to best approach capturing the actual and representative behavior of self-tracking users. I came to the conclusion that it would be valuable to follow a new user during his or her first time with an activity tracker, such as the Jawbone UP, because this sheds light on how the initial experience evolves in relation to both performance and engagement with personal data. The initial action was to invite individuals to wear the device and gather data on the behavior, and then they would answer questions on their perceptions of the experience. The participants had to be entirely inexperienced users who had not previously worn or been acquainted with a self-tracking device. The focus was on the new user, as he or she might have exhibited different considerations and behavior than those who have willingly pursued the

self-tracking from the start. For the study, the fact that the user wears a Jawbone UP means that it is possible to collect step, sleep and other lifestyle related activity data, such as workouts, food intake and mood. Step and sleep data are automatically recorded when the user wears the device, whereas other activity data is registered manually by the user in the accompanying mobile app. Moreover, a pilot study was done prior to launching the main study to test the design and make alterations to improve the overall study. A field study that included such data made it possible to discuss perceptions and experiences contra to the personal performance.

The study gathers both qualitative and quantitative data. The quantitative data is gathered through a pre-survey, the step and sleep data from Jawbone UP and the RescueTime interactions. The quantitative data is collected through the Jawbone UP app and RescueTime app whereas the pre-survey was manually answered. On the other hand, the qualitative data are semi-structured post-interviews that were conducted with all of the study participants. The method of analysis was done with SPSS with the quantitative data, while the qualitative data was analyzed through MaxQDA, which is a mixed method tool.

Another consideration was to perform an experiment, but it did not seem suitable to place the user in an experimental setting. An experiment has its limitations, for example, it cannot fully reproduce all the details of the social setting of scrutiny, but it will always contain traces of those who design the research setting (Webster & Sell, 2007). Thereafter, to study a self-tracking process, the user must wear the device for a longer period of time, and a lab environment with this research project's limitations cannot accommodate the desired observation period of 21 or more consecutive days. Moreover, experiential computing is concerned with everyday devices, which does not make it fitting to place the experience of the device in a deliberately constructed setting, but rather study it in the empirical world. The conclusion is that an experiment, be it a lab experiment or anything similar, was not suitable for the purposes of this study, while a field study fulfilled the criteria.

A more detailed account of the method and procedure of study 1 are presented in the forthcoming chapter.

4.3.2 Study 2: Interview study with experienced users

The second study continues the exploratory mixed method approach and conducts 54 in-depth semi-structured interviews with a purposive sample of experienced users of self-tracking devices, both Jawbone UP and Fitbit. The study aims at exploring the experienced user's perceptions of the self-tracking activity.

The format of semi-structured interviews was chosen because the interviews allow the researcher to gather data on identified issues but still offers the opportunity to raise new perspectives (Gubrium and Holstein, 2002). Qualitative research has been done extensively in IS research, as well (e.g., Keogh et al., 2006; Mantzana, 2007). Moreover, both entirely structured and unstructured interviews are dismissed for the purposes of this study. Structured interviews are not relevant because they do not allow the flexibility to explore the topic to the same extent as a semi-structured interview. Instead, structured interviews allow little to no flexibility and use an established format, which is relevant when there is solid understanding regarding the topic and detailed feedback is desired to understand specific issues. However, as previously noted, the user's perceptions on self-tracking is an emerging research context and therefore this project suggests that a more exploratory approach is beneficial to develop further understanding (Gubrium & Holstein, 2002; Wilson, 2014). The semi-structured interviews were therefore conducted based on an interview guide that was informed by study 1. This research project therefore acknowledges that building an understanding of the reality of this research interest requires an exploratory approach, such as a semi-structured interview approach. Once the data gathering phase brings understanding and the theory is set, a more structured approach can be applied to the research (Wengraf, 2001), such as that applied in Study 2.

In the interview study, the scope is narrower when compared to study 1 and focuses on exploring the perceptions of the experience of self-tracking. It also proceeds with an exploratory view and asks 'Why' and 'How' questions (Berg & Lune, 2004). The participants are experienced users because they have chosen to engage in self-tracking for longer than 2 months, of their own free will and without interference from the research project prior to the interviews. Despite no prior interference, it is still possible that the user might reconstruct or change perceptions of the usage in relation to the actual performance measurements, which were able to be tracked in the previous study. However, the philosophical

assumption outlined in this research approach accepts this potential shortcoming, since it assumes that the individual's understanding is limited and can only rely on the environment for knowledge, without fully understanding the real realm.

The method of analysis of the qualitative data collection was done by employing a thematic analysis. This methodological approach was chosen because it is important that the data is analyzed in an organized way (Attride-Stirling, 2001; Huberman & Miles, 1994). As this study strives for interesting and accountable results, the method of thematic analysis was adopted (Braun & Clarke, 2006). Thematic analysis is a method that helps "identifying, analysing, and reporting patterns (themes) within data" (ibid, p.6). It allows for an organization and interpretation of the data. Notably, some argue that thematic analysis resembles more of a tool that can be used across methods (Boyatzis, 1998). Yet, thematic analysis should be viewed as method, as it provides a framework for how the data should be managed and analyzed (ibid), while the software MaxQDA is the tool that enables this analysis. Neither is thematic analysis necessarily bound by a specific set of theoretical frameworks, but can be applied across several approaches, which proves its flexibility.

The thematic analysis consists of six phases: familiarizing with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes and producing the report (Braun & Clarke, 2006). These phases give a deeper view of the work that the researcher does when analyzing the data and therefore brings forward a possible way to evaluate, compare and synthesize it more carefully (Attride-Stirling, 2001). The process of working with a thematic method means that the researcher moves in and out of the data set, reads and repeats while coding and writing (Braun & Clarke, 2006). As such, the analysis requires the researcher be continuously involved in an iterative process. The writing and coding thus occurs at the same time as the analysis. The researcher plays an active role in identifying, choosing and highlighting themes of interest and then presenting them to the audience, rather than taking a passive role where the themes are claimed to emerge on their own. As mentioned, a main task during this type of analysis is to find themes. A theme "captures something important about the data in relation to the research question, and represents some level of patterned response or meaning within the data set" (Braun and Clark 2006, p.9).

Since the aim of this study is to reveal the user's understanding of experience and perceptions when the user is exposed to the personal data collected through self-tracking, there is an interest in being able to identify sub-tones and nuances that occur within this process. There is also an interest in any reactions and revelations that are come with being exposed to data about the self. By gaining access to data about the experienced user, this research project hopes to contribute insight and knowledge on how the user's perceptions are influenced by experiential computing-related practices.

A more detailed account of the method and procedure of study 2 are presented in a forthcoming chapter.

4.3.3 Two types of activity trackers

The studies involve the activity trackers Jawbone UP and Fitbit, and each one provides data on both steps and sleep. The two brands had public launches in the winter of 2011.

The Fitbit devices are available as either wristbands or clips that can be attached to clothing. The different types of clips are called Fitbit Ultra, Fitbit Zip and Fitbit One. The first wristband, the Fitbit Flex, was presented in 2013. Since then, the Fitbit Force was introduced but immediately retracted, only to later launch the Charge, Charge HR and Surge. The last two can track heart rate. All Fitbit devices, except from the Fitbit Ultra, have some sort of screen that visualizes the daily step count in various ways, e.g., the growing stem of a flower. The Fitbit devices also have a bluetooth syncing option, which allows seamless uploading of data to your smartphone or desktop, if it is bluetooth enabled. Only users of the same wristband, i.e., the Fitbit Flex, are interviewed, and other non-wristband Fitbit devices are not included, to keep the population consistent.

Jawbone has produced activity tracking wristbands since its launch in 2011. The first generation of Jawbone UP wristbands experienced extensive issues with the hardware. The second generation, also called Jawbone UP, had a widespread success yet lacked a wireless syncing function. This function was introduced in the third generation wristband, named UP24, in late 2013. A fourth generation is called Jawbone UP3 was introduced in late 2014 and started shipping in 2015. The

Jawbone devices used in the field study are Jawbone UP wristbands of the second generation. At the time of initiating this dissertation in 2012, these wristbands were the only ones available in Europe (Jawbone News and Press, 2015).

The features of the two different devices are illustrated in an overview below.

	Fitbit Flex	Jawbone UP
Step tracking	X	X
Sleep tracking	X	X
Food tracking	X	X
Mood tracking	X	X
Wristband display	X	
User owns personal data		X
Premium membership scheme	X	
Social network	X	X
Bluetooth	X	
Compatible with Android	X	X
Water resistant	X	X
Battery > week	X	X
Lower price	X	

Table 6. Comparison between Fitbit and Jawbone UP.

Notably, the self-tracking devices are different brands, but have similar qualities and functionalities. Both can be worn as a wristband and preferably around the clock. In return, the device automatically tracks activity and sleep that is based on

the user's behavioral pattern. The data is collected through sensors that are incorporated into the design. The hardware consists of several sensors, such as a motion sensor and a vibration sensor. The sensors activate through electromechanical elements when acceleration in speed and direction is detected, which is then translated into step or sleep activity. After the data has been collected, it is processed and visualized automatically in the accompanying software, available both as mobile and desktop solutions. The most commonly used solution is the mobile app. Within the app, any movement activity is presented as number of steps while sleep is showcased as hours and minutes.

4.5.1.1 Using the device and the app

When the device is activated for the first time, it is done so alongside the app. The user is prompted to enter the daily goals for both step and sleep activity. The app has a preset recommendation goal—10,000 steps and eight hours of sleep, respectively. However, the user may adjust these goals upward or downward at any point in time from within the app. The daily goals are updated by synchronizing with the wristband, and depending on which generation it is, this is done by connecting the device to the mobile unit or else wirelessly. Fitbit Flex synchronizes automatically while any Jawbone UP updates are done manually by opening the app and connecting the wristband to the phone.

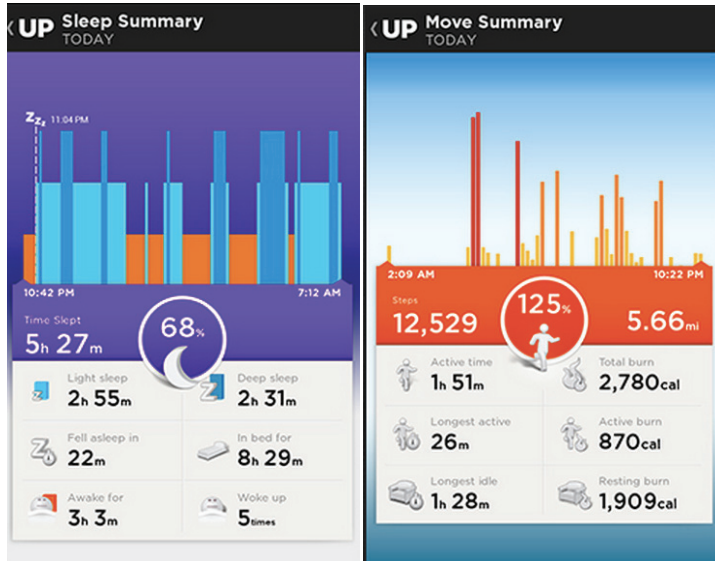


Figure 8. Jawbone UP interface for steps and sleep.

As soon as the user open the app, the latest measures of performance are immediately displayed on the front of the app home page. The Fitbit and Jawbone UP interfaces are slightly different in visualization but predominantly show the same type of data. This is illustrated in the shape of bars and percentages, one for activity and one for sleep. For example, if a user has set a daily goal of sleeping eight hours and has achieved this or more, then the sleep bar will show 100% or more. If the user wants additional information on the sleep, such as sound sleep, light sleep, time to fall asleep, then the user simply taps on the bar and will be led to a more detailed overview of this data. The same breakdown of data applies to activity where the user can see active time, longest active, longest idle, and calorie burn. The user is able to compare the collected data against each other, such as light sleep versus activity levels.



Figure 9. Fitbit interface for steps and sleep.

The apps provide additional data collection beyond activity and sleep. For example, food logging is integrated, which requires that the user manually log any food intake. Another manual feature is that the user can log workouts, such as weightlifting, swimming or dancing. The added value of such workout input is that the step activity chart attains a more detailed overview, for example calorie burn and active time. It is also possible to attach other mobile apps to the UP app so that this data is fed into the UP app. For example, the app RunKeeper can be attached to the Jawbone, which adds to the Jawbone activity data. Another feature is the smart sleep alert that allows the user to input what time they would like to wake up. For example, the user may want to wake up between 07.00 and 07.30 am and will manually enter this into the app. Based on the user's sleep data and patterns, the UP will gently vibrate at the time it calculates is the most optimal wake up time.

Both devices have a social component, which means that it is possible to invite other Jawbone UP users. If the other user accepts, the connection establishes the possibility for the users to see each other's data in their daily feed. However, any user can choose to lock any or all of the data, preventing it from being seen by

other users even when they are connected. For example, a user may not want to share sleep data and can lock this data permanently, or just select individual days.

4.5.1.2 Key differences between Jawbone UP and Fitbit Flex

The devices have many similar features but three key aspects distinguish them: data export, data deletion and display. In the first study, the Jawbone UP is chosen as the self-tracking tool of choice after evaluating these criteria.

Jawbone offers limitless data export, while the same action by Fitbit requires a “premium membership” of 40 USD per year. As a premium member, additional features are also accessible, but all primarily relate to the versatility of accessing and exporting the data. As a start, a premium member can export the data in CSV or XLS files. The personal data can also be placed in context with other users so the user can compare his or her statistics with the overall Fitbit population. However, the Jawbone UP data is always accessible by the user, without the need of a paying membership. The Jawbone UP user simply needs to log onto the account and download the CSV or XLS file. This was more affordable for the research budget, as there was barely any difference between Fitbit’s premium membership and the regular Jawbone UP membership.

The Jawbone UP user may at any time choose to delete personal data, whereas Fitbit’s policy is less transparent and more difficult to delete. The Jawbone UP user merely logs into his or her account and then clicks the button that reads “Remove all my data”, which then deletes all the data. Jawbone.com (2015) writes, “Jawbone respects your preferences. And so do our API partners. This form enables you to notify Jawbone and the partners that you would like your data deleted.” However, the Fitbit user must delete individual entries, such as steps of a particular day and then sleep of a particular day, and so on. As the first study is collecting personal and sensitive data about individuals, it is imperative that the participant’s data is being protected, due to national regulations. This is especially important in the event that a participant chooses to withdraw from the study, which means that all data must be deleted. Due to the difficulties of deleting Fitbit data, the Jawbone UP was considered to be a more trustworthy option in protecting the participant’s personal data.

The Jawbone UP wristband does not have a display, whereas the Fitbit Flex wristband has a minimalistic display. The Fitbit Flex has five dots on the display that indicate how far along the user has come towards the daily step goal. For example, when the user has reached 40% of the daily goal then two dots out of four are shown, if the user taps the wristband. The screen is a visualization of the data and gives the user an indication of the daily achievement. However, in the study, I could not find a way to control how many times per day a user reviews the dots on the Fitbit Flex wristband. On the other hand, the Jawbone UP requires the user to check the mobile app, which means that it is possible to measure how many times a user opens the app, by using the right software. This will be discussed later on in the forthcoming software section. The Jawbone UP wristband was thus chosen as the device for the field study, since it complies fully with the Danish Act on Processing Data.

4.4 Chapter summary

This chapter presented the methodological considerations and empirical studies that guide this research project. The departure point lies in critical realism, which has an objective ontology and a subjective epistemological perspective. This philosophical foundation views reality as fixed, yet a complete knowledge and understanding of this reality is not possible due to the limitations of the individual. Therefore, the individual only has a possibility of understanding the empirical world and based on the experiences in this world, speculations can be made about the real world. This perspective is compatible with a mixed method research. The mixed method has a sequential design, which means that it begins with a quantitative study that is followed by a qualitative study. Finally, the outline of these studies are introduced.

5. STUDY 1: NEW USERS

5.1 Introduction

The first study is a field study of new self-tracking users that consists of a pilot study and a main study. The pilot study is a field study with 13 participants who wore the Jawbone UP for 21 days. The main study consists of 34 participants who wore the Jawbone UP for a minimum of 21 days. According to Maltz (1989), habit formation requires a minimum of 21 days, and thus the participants were required to participate for a minimum of this duration. The study has both purely quantitative elements, such as performance measures of steps and sleep gathered by the experiential device, and qualitative elements, such as post-study-interviews with the participants. The quantitative elements were analyzed with SPSS, while the qualitative elements were analyzed through MaxQDA. The main question is: How do new users experience and perceive the practice of self-tracking in terms of personal performance? The table below gives an overview of the main study.

Main study	
Study type	Quantitative with qualitative elements
Sample	34 participants
Method	Field study
Data	Quantitative performance data from Jawbone UP Qualitative data from pre-study-questions and post-study-interviews
Research question	How do new users experience and perceive the practice of self-tracking in terms of personal performance?
Gender distribution	19M / 15W
Analysis	Statistical analysis and thematic analysis
Activity tracker	Jawbone UP (second generation)
Software for data collection	Jawbone UP app RescueTime
Software for data analysis	Quantitative: SPSS Qualitative: MaxQDA

Table 7. Overview of Study 1.

The chapter starts by presenting the hypotheses on both step and sleep performance. Thereafter, the data collection is presented, since there are several types of data gathered by the study. Then, the pilot study is presented, which brought insights and implications leading to changes for the research design of the main field study. Next, the field study is presented alongside details such as sample, recruitment, and procedure. This is followed by the findings of the study. The chapter sums up with the limitations encountered.

5.2 The hypotheses

The model and related hypotheses are based on the functionalities and features that are an integral part of the self-tracking device's design. The study focuses on investigating how the functionalities of the device affect the participant's personal daily performance in relation to the steps and sleep. The data surrounding these functionalities are tracked and collected entirely through the Jawbone UP app and the RescueTime app. Therefore, the model is specifically tailored to the Jawbone UP device and its functionalities as a self-tracking device.

This study involves two linear regressions, each related to steps and sleep, respectively. They are different activities with different goals set into the device. This means that step performance might be satisfactory whereas sleep performance is not. Moreover, the different activities also differ in how the participant is able to influence the performance outcome. For example, the participant can actively choose to take a walk around the block to get more steps, whereas it is more difficult (though not impossible) for the participant to actively choose to fall back asleep for another hour to improve the sleeping statistics.

The hypotheses of the linear regressions are grouped into three categories: behavior, engagement and social elements. These categories are based on the functionalities stemming from the self-tracking device. As an outset, the behavior category concerns the participant's performance that is captured by the device and then showcased as personal data in the app. It is thus actual behavioral measures that are embodied by the technology, as described by Yoo (2010). The behavior category is addressed first because it is the behavior that achieves a high success in relation to the performance goal and therefore, it is likely that the behavior has a great influence.

The engagement category is related to the user's participation and interaction with the mobile app and data. The role of engagement is an important part of this study because it has been identified in the theoretical background. More specifically, engagement with personal data is identified to support the process of self-reflection, which in turn has a positive influence on behavior, such as performance measures like steps and sleep (e.g., Consolvo et al., 2009; Li, Dey, & Forlizzi, 2012; Lin et al., 2006). Although engagement can take several forms, most importantly it includes the exposure of data to the participant. In this study, engagement is thus understood as participation with the personal data offered by the app that is related to the self-tracking device (Choe, Lee, Lee, Pratt, & Kientz, 2014; Sjöklint, Constantiou, & Trier, 2015). It is thus understood as having both interaction with and observation of the data.

The social category involves the social aspects available through the device, such as the user inviting other users to see the data and in turn being exposed to their data. The social element is important to discuss, for it is argued that it has an influence on the participant, who feels pressure and need to conform to the behavior and expectations of others, which could influence performance (Aaronson et al., 1994).

As an overview, the following are the hypotheses relating to step performance:

H1: Being active has a positive influence on the step performance.

H4: Checking the app has a positive influence on step performance.

H6: Increasing the step goal is negatively associated with the step performance.

H8: Notifications are positively associated with step performance.

H10: Social connections in the mobile app have a positive influence on the step performance.

The following are the hypotheses relating to sleep performance:

H2: The amount of deep sleep has a positive influence on sleep performance.

H3: Going to bed before 23.00 has a positive influence on sleep performance.

H5: Checking the app has a positive influence on sleep performance.

H7: Increasing the sleep goal is negatively associated with the sleep performance.

H9: Notifications are positively associated with sleep performance.

H11: Social connections in the mobile app have a positive influence on the sleep performance.

5.2.1 Behavior

The first category involves the behavior of the user, which is captured and embodied by the self-tracking device. When it comes to steps, the Jawbone UP records the steps, but also when the steps stem from an activity, such as taking a run, or those that are in an idle setting. As for sleep, the Jawbone UP records sleep phases, such as light sleep versus deep sleep and whether the user woke up during the night.

5.2.1.1 Step related behavior

The second category is behavior and includes user activity. The user's lifestyle in relation to the level of activity is likely to have an impact on the step performance. For example, adults who have a history of being physically active in their youth are 2-3 times more likely to be active as they age (Dishman, Sallis, & Orenstein, 1985). Consistent activity is thus an important part of staying active. This is also reflected in the use of an activity tracker, such as a pedometer, since the users who are initially leading an active lifestyle are more likely to perform better compared to those who have led more sedentary lifestyles (Tudor-Locke et al., 2004). However, it has also been shown that those who were not physically active but had a desire to change also increased activity that was sustainable over time (J. J. Lin et al., 2006). Overall, user activity is associated with both intrinsic and extrinsic motivation, which means that the user may already be active before wearing a self-tracking device, yet still gain motivation from wearing it (Li, 1999). The hypothesis is as follows:

H1: Being active has a positive influence on the step performance.

5.2.1.2 Sleep related behavior

Deep sleep is one of the indicators of the quality of the user's sleep session. While asleep, we go through several phases, which can be generally referred to as light sleep and deep sleep. Light sleep is usually 55% whereas deep sleep is 20% of the

sleep duration (K. A. Lee, Zaffke, & McEnany, 2000). The deep sleep is important for the person to feel more rested the next day (Horne, 1990). Deep sleep is thus an essential part of sleep and occurs in cycles, which means that more deep sleep generally means a longer sleep session (Babloyantz, 1986). The Jawbone UP app's sleep functions automatically measure the phases of deep sleep and showcase this to the user upon request. The accuracy of the measurement may be debated (Rettner, 2014), yet this study focuses on what occurs during and after exposure of the data, so the importance is placed on the fact that the device is consistent in its capture and reporting to the user. A longer period of accumulated deep sleep is considered to be an important indication that the user has slept for a longer duration, and therefore performs better. Therefore, the hypothesis is:

H2: The amount of deep sleep has a positive influence on sleep performance.

The exposure to sleep data may cause the participant to gain awareness that leads to changing behavior so as to perform better on the sleep measurements. This is because engagement with the data can help individuals to "increase their awareness and encourage healthy behavior change" (Choe, Consolvo, Watson, & Kientz, 2011, p.3060). This inspiration for behavioral changes may be going to bed early or at a consistent time, in favor of getting a better sleep experience (Stepanski & Wyatt, 2003). A study showed that going to bed at 23.40 was too late and associated with a decreased quality in the sleep experience (Buboltz, Brown, & Soper, 2001; Buboltz et al., 2009). Therefore, the hypothesis is:

H3: Going to bed before 23.00 has a positive influence on sleep performance.

5.2.2 Engagement

The second category is engagement and includes hypotheses regarding variables such as checking the app, changing goals and notifications. The data collected on these variables all stem from participation and interaction with Jawbone UP functionalities.

5.2.2.1 Checking the app

The first step of engagement with the personal data occurs by simply checking the Jawbone UP app. The Jawbone UP is understood as a commitment device that

helps the participant to act more deliberately and consciously—it reminds the user of the initial commitment (Ariely & Wertenbroch, 2002; Milkman et al., 2008). In this study, the Jawbone UP is thus a commitment device where the user commits to a more active lifestyle through steps and sleep. By wearing the device, the user is encouraged to act more deliberately by collecting and subsequently checking the personal data gathered by the mobile app. This is because checking the data leads to greater awareness of personal behavior and influences the user to do what should be done, rather than what he or she wants to do (ibid). The influence of different types of commitment devices has been studied in a self-tracking context, as well. For example, a study on the use of pedometers argues that wearing a self-tracker that shows the user personal data leads to activity increase (Chan, Ryan, & Tudor-Locke, 2004; I. Li, 2012). Therefore, the hypothesis is:

H4: Checking the app has a positive influence on step performance.

Using the same assumption as above, sleep performance is also believed to be influenced by continuously checking the app. For example, one study showed that becoming more aware about sleep patterns led to sleeping better because the individual made changes to his or her lifestyle (Stepanski & Wyatt, 2003).

H5: Checking the app has a positive influence on sleep performance.

5.2.2.2 Changing the goal

Moreover, changing the goal can have alternative effects on the personal performance, depending on whether the performance is increased or decreased. For example, this study asserts that changing the goal by increasing it has a negative impact on the personal performance because it becomes more difficult for the user to reach it. A study on step goal-related behavior showed that the user might be inspired to change the goal upward alongside recently increased activity. At the same time, the user's activities and practices may change in such a way that the goal is not met, even if the user is behaving more actively overall (Fritz et al., 2014). For example, if a user takes on yoga, the user is becoming more active, yet the added activity might not match the increased step goal. The pilot study showed that the users were hesitant to decrease the goal, but considered increasing it. Based on these considerations, the hypothesis is:

H6: Increasing the step goal is negatively associated with the step performance.

On the basis of the discussion above about step goals, the same assumption is adopted for sleep-related goals. The hypothesis is thus:

H7: Increasing the sleep goal is negatively associated with the sleep performance.

5.2.2.3 Notifications

The Jawbone UP has the functionality of sending the user different types of notifications about steps and sleep. In a self-tracking context, notifications are argued to be a useful reminder to users to do a task (Fogg, 2009). Another study support this idea and extends it by endorsing the power of mobile notifications to situations where users are encouraged to manually log behavior and performance as well (Bentley & Tollmar, 2013). The notifications are helpful to get the user to do something by bringing greater awareness. As a result, in this study notifications are argued to be useful for bringing awareness to the user to do the tasks related to the Jawbone UP. Therefore, the hypothesis is:

H8: Notifications are positively associated with step performance.

On the basis of the same considerations, the assumption is applied to sleep performance as well. The hypothesis is:

H9: Notifications are positively associated with sleep performance.

5.2.3 Social elements

The third category incorporates the presence and possible influence of social elements on users. The social data is collected by viewing the user's account and identifying how many other users have been invited to share the data. The social elements can be considered a type of engagement with others and their data.

The incorporation of social connections can contribute by adding motivation for the user to be more active as a response to social pressure. The presence of another

user may influence the self-tracker to strive towards being accepted, according to the norms existing in the setting (Aaronson et al., 1994). A study on social pressure showed that people were indeed more prone to comply with any formal or informal codes in the presence of others, yet also less inclined to comply when others did not (Wogalter, Allison, & McKenna, 1989). In a self-tracking context, collective use is shown to offer social support (Ploderer et al., 2014). Therefore, the hypothesis is:

H10: Social connections in the mobile app have a positive influence on the step performance.

Using the same background as social and steps performance, social influence has been argued to provide motivation for the user to conform to the contextual norms. In a self-tracking context, social factors may also influence sleep performance, as in the user making some attempt to synchronize times with other people who are around (E. Choe et al., 2011). As sleep data is considered very private, it is important to find the right community to share it with (Fritz et al., 2014).

H11: Social connections in the mobile app have a positive influence on the sleep performance.

5.3 Data collection

The data gathered in this study thus has a two-fold nature: examining the performance, and examining the experiences or perceptions of the experiences, as described by the participants. The table below presents an overview of the different types of data collected.

	Perception data	Performance data
Pre-study	Pre-study-questions about self-perception on steps and sleep	-
During study	-	Performance data on steps and sleep activity
Post-study	Interviews on the perceptions and experiences of self-tracking	-

Table 8. Overview of performance and perception data collected.

The data consists of 849 observations of behavioral data on physical performance, such as step and sleep activity. The step activity includes the accumulation of steps during the day but also involves subcategories such as active time versus idle time. The sleep activity encapsulates the duration of sleep, but also the light versus deep sleep. The sleep activity also automatically measures when the user goes to bed.

The performance data gathered by the Jawbone UP is transferred to the smartphone so that the participant can view the personal data. The engagement with the personal data is also collected, with the help of RescueTime, software that measures when the user opens the app. This enables the study to gather data on how often the user opens the Jawbone UP app to review the data. So the Jawbone UP gathers data on the physical performance while the smartphone app tracks the engagement with the data.

In order to perform the investigation of step and sleep performance, the following data was collected about steps and sleep. The variables indicate the name and abbreviation used. The description column describes how it was measured. The table below gives an overview of the measurements collected that are included in the regression analysis.

Category		Variable	Description
Steps	Engagement	Number of times app was checked daily (APP)	Measured between 0 and 10 times per day
		Changed goals (CG)	Measured with binary scale, no=0 yes=1
		Notifications (NOT)	Measured between 0 to 3 types of notifications
	Social elements	Social connections (SOC)	Measured between 0 to 1 social connections. No participants had more than one user included.
	Behavior	Active Time (ACT)	Measured between 0 to 10 hours per day
Sleep	Engagement	Number of times app was checked daily (APP)	Measured between 0 to 10 times per day
		Changed goals (CG)	Measured with binary scale, no=0 yes=1
		Notifications (NOT)	Measured between 0 to 3 types of notifications
	Social elements	Social Connections (SOC)	Measured between 0 to 1. No participants had more than one other user included.
	Behavior	Deep Sleep (DS)	Measured between 0 to 7 hours per day
		Bedtime before 23.00 (BT)	Measured with binary scale as yes or no.

Table 9. Overview of the independent variables.

The other type of data is qualitative data, that is, perceptions through narratives. This data is gathered by semi-structured interviews that ask the participants questions about experiences and perceptions prior and post study. The questions before the study asked about the participant's self-perception in terms of steps and sleep. The questions after the study sought to further understand the experiences the participant had with the self-tracking device.

5.4 Pilot study

This part of the empirical investigation is a pilot study with the aim of evaluating the initial research design and its advantages and disadvantages. It is a trial run with a smaller number of participants and reveals any imperfections in the design (Cozby & Bates, 2009, p.177). The pilot study is essential because it evaluates and potentially improves the research design prior to launching a full-scale study (Krishnaswamy et al., 2009). When the shortcomings have been identified, it is possible to make changes that may benefit the rigor and outcome of the study when it is launched in full scale. As expected, the Jawbone UP pilot study provided valuable insights and brought forward issues, such as the formulation of questions, survey timing, use of the instruction manual and device feedback.

5.4.1 Pilot study: Sample and recruitment

13 participants received the Jawbone UP wristband for the duration of 21 days or more (Maltz, 1989). The participants were all Danish nationals between the ages of 25-35 and all of them were working professionals. There were 7 males and 6 females. The participants committed to wearing the wristband all day and every day, as well as answering the daily survey questions that were sent as text messages to their smartphones.

The participants were recruited online for the study through forums and social media groups. Possible participants were given a link that led to an online sign up sheet, where individuals would enter their name, gender and email. After this, individual names were randomly selected and sent emails about the possibility of participating in the pilot study. In order to be considered for the study, each participant had to be completely unfamiliar with self-tracking previously and had

to have access to a personal smartphone on an iOS or Android system, with an uninterrupted internet connection. The pilot study was conducted in Denmark where the smartphone penetration is 59% and therefore it was a relatively easy task to recruit participants with this requirement (Our Mobile Planet, 2014).

5.4.2 Pilot study: Procedure

An invitation to a one-to-one meeting was sent out. At the meeting information was shared, a contract was signed and the participant installed the necessary apps and settings on his or her smartphone. The researcher, myself, met singlehandedly with each participant to provide a handbook, a brief introduction to the self-tracking device, an explanation of the study process and also to book a date for the post-study-interview when the study was completed. Then, the actual trial period proceeded, wherein the participant wore the wristband and received one to three daily survey questions via text messaging.

Participation in the pilot study was anonymous and voluntary. The participant could at any time and without giving any reason withdraw from the study. The data that had been collected up until this point would be discarded or given to the participants. Every participant had access and ownership of the collected data throughout the study, as well as afterwards. In order to sustain such confidentiality, each participant signed a combined letter of consent and privacy statement, which I then co-signed, since I was the study coordinator. The pilot study collected several types of data from the participants: participant activity and sleep (through the Jawbone UP), participant survey responses and a participant post-study-interview. A more detailed review of the data collection is presented later on in this chapter.

To ensure anonymity during the data collection, each participant was assigned a unique identity for which the data would be collected and organized. Each identification number started with QS (abbreviation for Quantified Self), with two random letters and two random numbers added, for example, QSCD14. The identification number was used for the email address, for example, QSCD14@gmail.com. The unique email provided access to two accounts of the two necessary apps, Jawbone UP and If This Then That (IFTTT). These two mobile applications were needed to collect data and administer the daily survey

questions. Each participant downloaded the apps and logged on with the assigned email and thus ensured the data collection. At this point in time, the research design required that the necessary data be collected from both apps.

The participant received between one and three text messages every day. The survey questions were sent out as text messages that contained the question and a link. The participant was required to click on the link that opened a survey form with a text box where the answer was recorded. In order to influence the participant's answers as little as possible, the only thing on the response page was the question and an empty, optional, text box. When the participant had recorded his or her answer, the answer was then sent to an online spreadsheet linked to the unique ID. All data collected by IFTTT individually assigned the data to different spreadsheets.

The following table presents the daily survey questions that were sent to the participants along with the options of response, how it was triggered and reasoning for asking the question.

Questions	Response options	Trigger
How are you feeling today?	Open ended Empty text box	The text message was triggered when a participant synced and logged sleep in Jawbone UP.
What are you doing for the rest of the day?	Open ended Empty text box Optional step count box	Triggered every day at 16.45, regardless of participant action
You've reached your step goal! So what are you doing for the rest of the day?	Open ended Empty text box	The text message was triggered when a participant synced and logged step activity in Jawbone UP that showed the daily goal had been met.

Table 10. The daily survey of the pilot study.

5.4.3 Pilot study: Software

There were two types of software involved in enabling the pilot study: the Jawbone UP app and IFTTT. The two mobile apps, Jawbone UP and IFTTT, both

collaborated and managed the delegation of the data in the pilot study. The Jawbone UP app was necessary for any Jawbone UP user, since it downloads the data from the wristband and visualizes the data to the user. The IFTTT app was included for the purposes of administering the daily survey questions and the data collection. The IFTTT is a platform that mediates a service that allows the administrator to program a commando for action. A commando could occur, for example, if a Jawbone UP user uploads data on last night's sleep activity to the Jawbone UP app. The IFTTT app must send this row of data to a designated Google doc spreadsheet. The same activity, i.e., uploading sleep activity, also triggered a survey question to be sent via a text message to the participant.

IFTTT was used for several purposes. Initially it was used to schedule sending certain types of data to a designated spreadsheet. Seven types of data were scheduled to be collected. The importance of this function was to retrieve the timestamp to indicate when different activities were exercised. The importance of the timestamp was that it would give an indication of how often a participant might check the Jawbone UP data. For example, every time the participant would sync the wristband, updates of sleep and activity would be collected and directly sent to a spreadsheet accessible to the researcher. Additionally, spreadsheet notifications would also be updated when the participant manually entered activities, such as workouts, meals and mood. Secondly, IFTTT was used to send three different types of questions to the participants.

5.4.4 Pilot study: Implications and improvements

The pilot study was successful, providing a great deal of feedback on how to improve the research design of the full-scale study.

IFTTT proved both useful and problematic, so the role of the software was adopted. The IFTTT was useful in sending out text messages with the daily survey questions to the participants with a Danish mobile number. However, if the participant did not have a Danish mobile number, he or she would not regularly receive the text messages sent by IFTTT due to a server issue with the IFTTT provider. This only had implications for one of the participants, who was subsequently omitted from the final sample. IFTTT was also problematic when it came to retrieving data from the Jawbone UP app that was subsequently supposed to be sent to a Google doc spreadsheet. IFTTT was not able to give the exact

timestamp indicating when the data had been updated. For example, consider a participant who updates his or her Jawbone UP app with step data three times during one day. This data is only shown as one row of data, rather than three. As a result, IFTTT automatically aggregated the data rows into one row and assigned a timestamp that was based on the latest sync time rather than the separate sync times. This meant that it was not possible to explore how often users updated and interacted with the data in the Jawbone UP app.

A completely new setup for retrieving data on the participant's app interaction was needed for the full scale study. The timestamps for when the participant checked the Jawbone UP data proved problematic in the current setup, both in retrospect and in real time. After lengthy correspondence with the Jawbone UP developer team and working with the Jawbone UP API, it became apparent that the data required could not be manually extracted without the help of a customized setup. In order to change this, a string of developers were contacted to write code, such as a customized webhook, which would allow the retrieval that the timestamps required. A majority of the developers declined and it proved too time consuming and expensive to do this, in the end. Therefore, an alternative option had to be found, such as the RescueTime app.

The daily survey was not answered regularly by the participants and so it is omitted from the full study, because the lack of data posed issues with reliability. The participants stated that their irregular answering was due to a failure to remember and to neglect, despite the fact that the participant had made a commitment via the contract to answer immediately upon receiving a text message. It should be noted that it was of interest to the original research design to have an immediate response as a way of checking the immediate reaction of a participant who had just viewed his or her personal data. However, this aspect was not reliable and had to be omitted.

A set of pre-study-questions should also be included to offer a departure point and identify expectations. A pre-interview is valuable to compare expectations, motivations and considerations (Cozby & Bates, 2012) before and after wearing the self-tracking device. In turn, this allows the study to make a comparison to the month long trial and the post-study-interviews. Furthermore, the interview form

was given on a one-to-one basis, and it is worth considering whether a focus group would be more appropriate to discuss experiences.

The handbook was not handed out to the participants in the full study. This change is a small but noteworthy aspect. Several participants mentioned in passing that they were not in need of a device handbook and considered that introductory meeting was sufficient enough. When additional questions popped up, the participant would search online for the response, rather than looking at the handbook.

5.5 Field study

This section presents the research design of the first part of the exploratory mixed method approach, namely the field study. This study is interested in how a person who has never engaged in self-tracking through an experiential device perceives the experience of collecting, measuring and being exposed to personal data.

The study engaged 34 participants to wear an activity tracker for a minimum 21 days to study the initial behavior period (Maltz, 1989). During the study, the participant wore the device. After the study, the participants took part in an interview. The study resulted in 849 observations of steps, sleep, and interaction with the personal data. In summary, the study followed users around the clock in everyday activities and measured this behavior by collecting steps, sleep and interaction data. Thus, the study collected behavioral data but also the level of interaction, for example, whether the participant usually checked the step count in the morning or evening.

The pilot study provided valuable feedback so that several improvements could be made. The main changes involved including pre-study-questions, adding new software for data collection, and creating an updated post-study interview guide. An overview of the study's process is presented in the figure below.

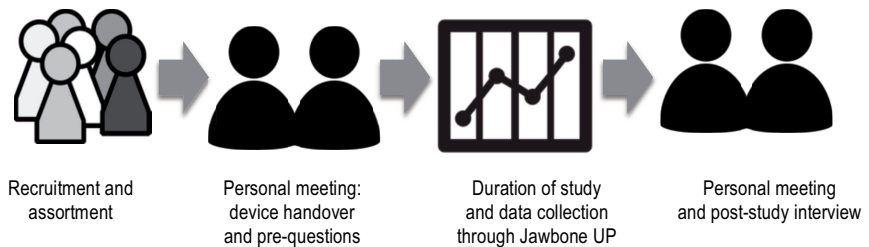


Figure 10. Overview of study 2.

5.5.1 Sample and recruitment

The participants were students at the Copenhagen Business School. Students were considered a relevant sample to study because they are avid users of technological devices, such as smartphones, and they are often referred to as digital natives, which is “a new generation of users who have spent their entire lives surrounded by and using computers” (Yoo, p.216). These users go beyond the traditional organizational user of IS research, which is necessary in a context where computing has become an everyday experience and has a stronger individualistic focus on the user (Lamb & Kling, 2003).

As stated, the majority of the participants were Danish nationals, with the exception of a few European nationals. All participants were living permanently in Denmark. All interaction with the participants, such as interviews, emails and information, was done in English. All the participants were comfortable with interacting in English, as their study programs were entirely in English, which led them to speak English on an almost daily basis. All of them considered themselves fluent in English. The sample details are illustrated below.

Participants	Male	Female
Age		
18-30	18	15
30-40	1	0
40-50	0	0
50+	0	0
Occupation		
Student	18	15

Table 11. Demographics of study 1 participants.

The recruitment was situated at Copenhagen Business School. As a recruiter, I attended various university courses with bachelor and master of arts students in which a brief presentation to the research study was made. At the end of the presentation, the students were invited to sign up to participate through an online link. The sign up was completely voluntary. The requirements for participation were that the student must be over 18 years of age, must not have previously engaged in self-tracking through activity trackers and must have access to a personal Android smartphone. All these criteria were presented in the recruitment presentation. Additionally, the participants were not offered an explicit incentive or compensation, such as movie tickets, to participate. This was omitted because of the possibility that it might influence a study that sought to capture the behavior of a novice in self-tracking.

More than 150 students signed up for the study but around 80 had to be excluded because they owned an iPhone rather than an Android. The remaining 70 students were contacted, but only about 50 of them responded to this contact. A total of 40 students participated in the study but four decided to withdraw before the term had finished. The data of two participants data had to be omitted because of issues of insufficient data; this was due to faulty devices or because they did not wear the device during the assigned period. A total of 34 participants successfully concluded the study. Notably, the study took place in two iterations because there were not enough wristbands to accommodate all 34 participants at the same time.

The Android restriction is essential to the study's data collection, for the software used to track the interaction with the Jawbone UP app was done exclusively with Android software, using the app RescueTime. There is no similar tool or software like RescueTime that works with iPhones, due to limitations posed by the iOS system (RescueTime Blog, 2014). Some other alternatives for the iPhone system, such as TimeDoctor, Toggl, Timr, and Desktimer were reviewed as possible options, but all of them required manual input from the participant. However, manual input is not as equally exact and precise as automatic tracking. For the purposes of this study, it is important to have automatic tracking of the participant's behavior to receive the most accurate interaction data possible. The Android smartphone requirement omitted a major group of potential participants—iPhone users. The iPhone is the most popular phone among university students in Denmark (Our Mobile Planet, 2014).

5.5.2 Procedure

The procedure for the study had several steps. As the research design differs from the pilot study, these are presented in detail below.

The participants signed up and were invited to a one-to-one meeting with the research study coordinator, which was me. At the meeting, the participant was presented with the letter of consent and privacy agreement followed by a description of the terms. The participants were encouraged to consider any questions about the data collection. After the mandatory signature, an identification number was assigned to the participant to ensure anonymity during the study. The participant was then given the device, the Jawbone UP, and prompted to install two apps, Jawbone Up and RescueTime. The identification information was also used to log into these apps. Once the practicalities had been settled, the participant was instructed to wear the wristband continuously and as considered appropriate during the study. For example, most users would take it off while showering, and some while doing impact sports (e.g., American football), for fear of breaking the device. The participant was also instructed to use whatever functions available in the app and device that they found suitable. This was in order to ensure that the participant would use the features he or she found most valuable and not feel restrained nor forced to log certain data, for example, food intake. If the participant had been instructed to use a specific set of functions, this

might have been an imposition that influenced the behavior and outcome of the experience.

The participant was asked four questions prior to starting the study. These questions were added after conducting the pilot study, and served as a complement to the post-study-interview. The importance of asking these questions was to get an understanding of how the participant saw him or herself in relation to activity levels and sleep patterns. The questions were asked because the self-perception might change between the start and the end of the study, as the participant is exposed to measurements of his or her performance. In the pilot study, these questions were not asked, so it was not possible to compare whether there had been any changes from the participant’s pre-study self-perception compared to the post-study perception. By asking the questions below, it might be possible to discuss and compare self-perception at the start and at the end of the study, respectively. The questions were given to the participant on paper and then the interviewer asked “Do you consider yourself active?” and “Do you consider yourself a healthy sleeper?”. The wording was purposely formulated as to ask whether the participant considered him or herself active, rather than if she or he is healthy. The same rationale went into the second question by asking if the participant was a healthy sleeper, rather than a good sleeper. None of the participants had follow-up questions on the survey, but all of them answered immediately.

Category	Questions	Response options
Activity	I consider myself an active person.	Yes / No
	How many times a week do you work out?	#
Sleep	I consider myself a healthy sleeper.	Yes / No
	How many hours per night do you sleep?	#

Table 12. Pre-study questions.

After the study, the participant was invited to a post-study-interview. The post-study-interview was the last part of the study procedure and was conducted with

the purpose of gaining additional understanding about usage, influence and motivational aspects of the Jawbone UP. In this meeting, it was possible to ask the participant about what had been discovered in the data, how it may have been surprising (or not) to see and other experiences. It was also interesting to inquire whether the participant's expectations and self-perception of sleep and activity had been altered.

An interview scheme was developed based on the background of the discussions in the pilot study interviews as well as the theoretical background chapter. The interview scheme consists of the following categories: general experience, use, motivation, role of data, trust, notifications, social components and continued use. Due to the semi-structured interview approach, the categories and questions served as a departure point and consulting source. However, the binary questions were always asked.

The two first categories, Use and Goals, attempt to grasp a general understanding of the participant's use and application of the device. The Use-questions also serve as an accessible and easy entry point that the participant can easily answer, and thus feel comfortable doing so. The Goals category is relevant because it asks questions about the goal, which is an inherent part of the self-tracking device and app design (Cosley et al., 2012; Looock, Staake, & Thiesse, 2013). The category Goals then proceeds to pose two questions on a dichotomous scale. These were incorporated into the statistical analysis. In order to extend the understanding of these dichotomous questions, a question is asked about how the participant feels in relation to achieving or not achieving these goals.

The Experience category questions are asked to ascertain the background of the experiential computing which assumes that the participant is not experiencing the technology in itself, but that the experience lies between the user and the technology (Yoo, 2010). The questions are thus posed to understand the perceptions, experiences and stories that are related to using an experiential device.

The Data category is related to the exposure to personal data that occurs when the participant checks the Jawbone app. The first question is posed regarding trust, which is connected to the findings in the theoretical background discussion.

Evidence suggest that it is important for the user to understand how the data is collected, distributed and exposed through the tool (Huldtgren et al., 2014). The two other questions are posed as to allow the participant to elaborate on the first data question.

The Device alerts category contains questions that are asked to get functional information about the features that the user activated in the Jawbone. These were not available through the other data collection channels.

The Social elements category is of importance because there are social features available in the self-tracking device, but also from the theoretical background discussion. That background states that social influence is an important part of engagement with the data because it influences the participant's perception of personal data. It might also spur comparison and competition as well as the motivation to continue for the purpose of social approval and desirability (Adams et al., 2005; Tajfel, 2010).

The Continued Use category asks whether the participant would continue wearing and using the device. This question is frequently incorporated in adoption studies in IS, such as the expectation-confirmation model (e.g., Bhattacharjee, 2001) to study the continuance intention. The participant is encouraged to elaborate on why he or she would or would not continue to use the device.

Field Study Interview Guide		
Use	Describe a regular day with your Jawbone.	
	Why did you want to wear the Jawbone UP bracelet?	
Goals	Do you monitor if you have reached your goal? (Sleep and/or Steps)	Y / N
	Did you change any of the daily goals at any time? Why?	Y / N
	How does it feel when you <i>have</i> or <i>have not</i> reached your daily goals?	
Experience	How has your time with the Jawbone UP been?	
	Share a positive experience you've had with the Jawbone UP.	
	Share a negative experience you've had with the Jawbone UP.	
	By using a Jawbone UP, do you experience any influence on your behavior? If yes, how?	
Data	Do you trust the data? Place your trust on a Likert scale.	7-point scale
	What does the data mean to you?	
	What do you see when you look at your data?	
Device alerts	Have you used the Jawbone UP notifications?	Y / N
	Please specify: Smart alarm? Idle alert? Sleep notifications?	
Social	Do you have any social connections on the Jawbone UP mobile app?	
	Do you pay attention to the other people's uploaded data? Why?	Y / N
	Do you share your data on other platforms? If yes, why?	
	Do you discuss your results with anyone? Online or offline?	
Continued use	Would you continue using the device, if possible?	Y / N

Table 13. The post-study interview questions.

5.5.3 Software

In the full study, two software types were introduced to the research design in order to facilitate the needed data collection: Jawbone UP and RescueTime. This aspect was updated after the shortcomings of data collection stemming from the pilot study. The apps Jawbone UP and RescueTime were used to track and record participants' activity.

The study participants were required to download two mobile apps to participate in the study: Jawbone UP app and RescueTime. All accounts were activated with the identification number, email and password attached to the participant. The Jawbone UP is the mobile app that is most frequently used by the participant, as it uploads data and provides visualizations of the personal data. The RescueTime merely runs in the background and does not require any maintenance. However, both apps are essential, since they track, record and provide visualizations of the activity patterns of the participant.

The Jawbone UP app is the primary way for the participant to see and interact with any personal data that is collected by wearing the wristband. Beyond the mobile app, it is possible to log into the Jawbone UP account on a desktop browser but in this case, the data is only available in a spreadsheet form. As a result, the primary tool for the participants to view and interact with collected data is the mobile app (Jawbone UP, 2015). As the Jawbone UP app is the main mode of interacting the data, it is crucial to measure app usage to understand interaction, such as when and how each participant interacted with the Jawbone UP data. The Jawbone UP usage can be measured by the RescueTime app.

Secondly, RescueTime is a software tool that runs in the background of both desktop and Android mobiles to measure the time spent using different types of software and websites. Importantly, the tracking is done entirely automatically through the software, so there is no manual data entry from the participant (RescueTime, 2015). All that is needed is that the participant installs the app on his or her phone or desktop and the software proceeds to log time spent using the Jawbone UP app. The software logs time spent in different categories such as social media, communication tools and work-related tools. It also gives specific log reports about which apps and software is used, such as Facebook, Microsoft Word, or a local email program. For the purposes of this study, the Jawbone UP

report was the only RescueTime report of interest. This report gives an overview of what hour of the day the app was opened, how many times the app was opened during the day as well as the duration of the interaction. The report also gives insight into how many minutes are spent in relation to other apps. For example, 18 min of Jawbone UP app usage is 16% of the total time spent on the smartphone.

5.5.4 Privacy and identification

Participation in the full-scale study was anonymous and voluntary. The major change was the increased focus to communicate the participant's rights of privacy and ownership, as this is mandatory according to the Act on Processing of Personal Data of 2000. This act demands that the Danish Data Protection Agency is notified about what type of data is collected and how it is handled. As the research coordinator, I submitted this notification per the requirements. As a result of this procedure, the participant's rights were underlined at the start of the study so that there was full transparency on how the data was handled and protected.

The rights remained equally as rigorous as in the pilot study, but participants were more extensively informed in the full study. In every introductory meeting, the contract and rights of the participant was explicitly explained. Each participant was informed that he or she was still the primary owner of all the data collected during the one-month long study. By recognizing and signing the letter of consent, the participant gave the study permission to extract the data for the given period and to use it for the purposes of scientific research. The personal data may not be distributed, sold or shared with external sources at any point in time. However, the participant could at any time choose to withdraw from the study without reason and thus ask for the data to be erased. This happened three times in the full study.

The Jawbone UP was chosen, among other things, due to its diligent privacy policy surrounding user data, which means that the user owns the data at all times, and may easily extract and alternatively erase the data from the account permanently. On the Jawbone UP's website, it reads: "Jawbone.com, UP, and Partner Data Jawbone respects your preferences. And so do our API partners. This form enables you to notify Jawbone and the partners that you would like your data deleted" (Jawbone, 2014).

As with the pilot study, each participant was assigned an anonymous identification number that was used to collect the personal data. The unique identification number starts with the letters QS (abbreviation for Quantified Self) followed by the initial letter of the month of commencement (O for October, N for November) and finally, a participant number. For example, QSO15 represents the Quantified Self Study, the month of October and participant number fifteen. Each unique identification number is attached to an email with the prefix `qsprojectstudy`. In this example, the email would be qsprojectstudy+QSO15@gmail.com. Therefore, in the data collected by the study, the participant's name never was nor will be directly related, but remain anonymous.

The identification number and the related email are used for two different types of data collection and management: Jawbone UP and RescueTime. These are also further described in the following section. When the accounts are created, the password is also given to the participant, who can check the data collection at any point. The participant may opt to take over the account fully, by making changes such as updating to a personal email and password. Two participants have chosen to do so.

5.6 Pre-study: Self-perception on personal performance

The pre-study questions were asked to gain an understanding of the participant's self-perceptions activity and sleep patterns before engaging in self-tracking. It is relevant to pose these questions before the study when the participant has not yet experienced exposure to personal data, which could alter the perception. The answers are mostly likely to be intuitive and based on the experiences of current circumstances, as none of the participants had previously engaged in a self-tracking that exposes them to personal data. The pre-study questions suggested that the participants showcased a fairly similar self-perception when it came to step and sleep habits. The participants considered themselves as both fairly active on a weekly basis and healthy sleepers on a general basis. There were only a handful of participants who did consider themselves as not very active or not healthy sleepers.

The first question regards the participant's activity during a regular week. Active days were described as days in which the participant performs a workout or

exercise regime, such as weightlifting, playing football, basketball or a spinning class. The data shows that nearly 75% of the participants considered themselves active with a mean of 2.7 active days per week. Almost 13% of participants did not do any exercise, whereas 14.5% exercised as often as 5 times a week. The remaining participants resided in the middle of these two parameters.

The second question inquired about sleeping patterns. In this case, 72% of the participants considered themselves to be healthy sleepers. According to the participant pool report on sleeping habits, the mean estimate indicated 6.8 hours per night for the average person. Most commonly, the participant estimated that he or she got between 6 to 7 hours of sleep, but never more than 8 hours daily. However, the notion of calculating one's sleep is hard to estimate in the same way as step activity, so the participant was asked if he or she considered themselves to be healthy sleepers. This wording was chosen rather than "good sleeper", which could be confused with the quality of the sleep, such as having dreams, or waking up a lot or not.

SELF-PERCEPTION	N	Mean	SD	Min	Max
User considers themselves active*	849	0.75	0.44	0	1
Active hours per week	849	2.72	1.57	0	5
User consider themselves healthy sleepers*	849	0.73	0.45	0	1
Sleep per night	849	6.85	0.76	0	8

Table 14. Self-perception prior to the study.

5.7 During the study: The personal performance data

This section presents and focuses mainly the descriptive findings regarding the performance data, while the regression models and perceptions are addressed later on.

During the study, a wide variety of data was collected automatically regarding the participant's daily performance. The personal performance data consists mainly of two types of data, step-related and sleep-related. The step data is an active measure that the participants can actively engage and influence as it is in consciousness, while sleep data is an idle and stagnant activity performed

primarily outside of a conscious state. For example, the step result is a personal performance measurement that the participant usually can actively change by going for an extra walk around the block, getting off the bus a stop earlier or going to the gym. On the other hand, the sleep result is less susceptible to active change. The participant can opt to go to bed earlier, refrain from caffeine and other similar remedies yet an improved sleep result cannot be consciously and actively pursued in the same manner as the step goal. Beyond this, data on the interaction with the Jawbone UP app was collected, such as how many times the mobile app was checked and whether any additional activities were logged manually by the participants, such as workouts, mood, and food.

The daily step goal for the participants was most commonly 10 000 steps, as recommended by the mobile app. All participants entered and approved the step goal manually in the mobile app upon installing the app on their smartphone. When doing this, the Jawbone UP app makes a recommendation to set the daily step at 10 000 steps by referencing the National Health Association. The data collection shows that the participants' step goal ranged between 4000 steps and 13 000 steps, with a mean of 9783 steps as a goal per day. The mode, or the most common goal, was the recommended 10 000 steps, which accounted for 88.6% of the participants. Only 4.5 % of the participants had more than this recommended goal. If a participant chose to have a lower goal, there was a big drop down to 6000 and below, which only constituted 7%. In other words, the ones that lowered the daily step goal chose a considerable decrease from the recommended goal. Overall, the majority of the participants chose the recommended 10000 steps as the daily step goal and only a handful chose above or below this. When investigated, those that considered themselves to be active were not correlated with a higher step goal. These descriptive statistics indicate that the participant is likely to go with the recommendation provided by the mobile app and this became the standard by which the daily results were compared.

When it came to the results of daily step activity, the participants were active for an average of 1.6 hours per day with a standard deviation of 1.3. The range of steps was originally between a minimum of 112 steps and a maximum of 21 728 steps, with an average of 8869 steps. This suggests that activity levels ranged a great deal between days where the participant was extremely inactive or active a great deal. The great range of the data set suggests that the users do not exhibit the

same patterns of movement every day, but there are variations, which create such outliers. These may be due to the fact that the participant travels or is sick. However, some participants had continuously low step results because their routine was studying at home, which did not allow for more than a few hundred steps per day to be collected. Another participant had a low step score because of taking local transport and buses, rather than walking or biking. The performance data on steps showed that users have different movement patterns that range from being active to mostly idle on a daily basis.

CATEGORY	N	Mean	SD	Min	Max
STEPS					
Step goal	849	9782.82	1248.19	4000	13000
Step result	781	8869	4850.56	112	21728
Active Time (hrs)	800	1.58	1.25	0	10.3
SLEEP					
Sleep goal (hrs)	849	7.76	0.41	6.5	8
Sleep result (hrs)	630	7.0	1.74	1	11.6
Deep sleep (hrs)	630	3.15	1.25	0	7.4
Bedtime before 23*	849	0.16	0.36	0	1
ENGAGEMENT					
Times app checked	849	1.95	1.95	0	10
Changed goal*	849	0.14	0.14	0	1
SOCIAL					
Social connections**	849	0.25	0.25	0	1

Table 15. Descriptive statistics of study 1.

(*binary scale 0=no, 1=yes)

In terms of sleep data, the participant was also prompted by the device to enter a goal as she or he set up the mobile app, similarly to the step goal installation. The in-app recommendation is 8 hours. The sleep goal data indicates a range that varied from 6.5 hours to 8 hours of sleep with a mean of 7.8 hours of sleep and a mode of 8 hours of sleep. There was less range between the participants' sleep goals than between the different step goals.

The sleep results varied from between 1 hour of sleep to 11.6 hours of sleep. However, the sleep data is collected differently from the step data by the device. The sleep data collection is triggered when the participant enters “sleep mode” by activating a button on the device. As soon as “sleep mode” has been entered, the device measures how long it took for the participant to fall asleep, how long the participant slept, and also light versus deep sleep. Therefore, the result of no sleep is only recorded if the participant has forgotten to enter sleep mode prior to actually going to sleep, or ignored the process altogether. This is also representative in the number of logged sleep results (630 observations) compared to the number of sleep goal observations (849). The results show that both the average ($M=7.030$ hours) and mode (7.0 hours) were close to each other. In terms of bedtime, 84.3% of the observations fell asleep after 23.00. Whilst asleep, the deep sleep lasted an average of 3.2 hours. One participant managed to sleep an impressive 7.4 hours of deep sleep in an 11.6 hour period.

Overall, the female group had a higher mean average both in terms of steps and sleep when compared to the male population. In order to further investigate, independent t-tests were performed to review whether these differences were significant. The female group’s step results were associated with a higher step result ($M=9307$, $p < 0.05$) in comparison to the male group, which was associated with a numerically smaller step result ($M=8498$, $p<0.05$). In terms of sleep, the female group also got more sleep than the male counterparts. The female group had slept on average $M=7.4$ ($p<0.05$), compared to the male group that had numerically smaller sleep of $M=6.7$ ($p<0.05$). Thus, there were significant differences for gender between the step and sleep results. The females were also significantly different when it came to deep sleep ($M=3.7$, $p<0.05$) compared to the males ($M=2.8$, $p<0.05$).

5.8 Analysis of personal performance

The investigation of self-tracking of personal performance was done by performing two standard linear regressions, one for steps and one for sleep activity. A linear regression model presents an opportunity to predict the value of a variable based on two or more variables. This is ideal when assessing complex real-life investigation, rather than those that are laboratory-based (Pallant, 2002).

The purpose of the study is to investigate how the Jawbone UP functionalities influence the user's daily personal performance.

5.8.1 Step performance results

The dependent variable is calculated as the step performance. The step performance is a measure of the rate of performance in relation to the goal. The step performance is measured in the following equation:

$$\text{Step performance} = 1 + \frac{(\text{step goal} - \text{step result})}{\text{step goal}}$$

Based on the data collection and the hypotheses, the following model is proposed:

$$\text{Step performance} = b_0 + b_1 \text{ act} + b_2 \text{ app} - b_3 \text{ cg} + b_4 \text{ not} + b_5 \text{ soc}$$

The regression model indicates that $r^2 = 0.328$ with an adjusted $r^2 = 0.324$, which means that 32.8% of the variance may be explained by the independent variables. The small difference suggests that the variables are relevant for the model. In other words, 32.8% of the step performance is explained by active time, number of times the app was checked, social connections, changed goals and notifications. The relatively low r^2 is common in studies that involve human behavior and often give less than 50%, as human behavior is not necessarily predictable and consistent. In order to account for the low r^2 , there are significant independent variables in the model, which makes it possible to draw conclusions.

Variable	B	Std. Error Beta		t	Sig.
Constant	.631	.042		15.043	.000
ActiveTime (ACT)	.245	.013	.598	18.756	.000
Social connections (SOC)	.104	.033	.093	3.102	.002
Times app check (APP)	.029	.008	.112	3.690	.000
Changed goals (CG)	-.289	.046	-.203	-6.246	.000
Notifications (NOT)	-.067	.018	-.118	-3.812	.000

Table 16. The results of the regression analysis of the step performance.

The results indicate that the independent variables are significant as hypothesized. According to the regression model, it is possible to accept hypotheses 1, 4, 6 and 10. Hypothesis 8 was rejected because it is not positively associated with step performance. Instead, notifications have a negative influence on step performance, rather than positive influence as was initially hypothesized. As a result, the independent variables that predict the step performance are: active time (hours), inclusion of social connections, the number of times the app was checked, and negatively associated with changing goals and notifications. Therefore, the regression model is:

$$\text{Step performance} = 0.631 + 0.245 \times \text{act} + 0.104 \times \text{soc} + 0.029 \times \text{app} - 0.289 \times \text{cg} - 0.067 \times \text{not}$$

According to the results, having a high daily activity (0.245, $p < 0.001$) accounted for the strongest influence after controlling for the remaining variables, followed by the inclusion of social connections (0.104 $p < 0.03$). The engagement with the app, that is, the number of times it was checked daily, also had a positive effect (0.029 $p < 0.001$). However, changing the goals (-0.289, $p < 0.001$) and notification (-0.067, $p < 0.001$) had a negative influence on the step performance.

The amount of active time in the app accounts for a great deal of significant variance ($t=18.756$, $p < 0.001$). This suggests that the more the participant is active (and not idle, e.g., sitting still), the more likely he or she is to reach a better step performance. Then the inclusion of social connections further had a significant impact ($t=3.102$, $p < 0.001$). From this, the number of times the app was checked each day also accounted for significant variance in the regression ($t=3.69$, $p < 0.001$). This suggests that the more the participant checked the app, the better step performance he or she performed. These findings suggest that being physically active and interacting with the app, through checking the app and involving social connections, had a positive effect on the step performance. However, the variable of checking the app does not specify what the participant actually did while checking the app. The software, RescueTime, was not able to extract what the participant paid attention to or whether the wristband was synchronized to upload the data. The participants stated in the post-study-interviews that they would synchronize the data every time they opened the app to have “the latest and freshest information” (QSN10, 24, male). This statement brings attention to the

likelihood that the user will update the data, yet still does not clarify what pieces of information took up the user's attention while checking the app. This is further discussed in forthcoming sections on the user's perceptions.

A change of the daily goal and notifications indicated a negative impact on the step performance. A change of the daily goal was associated with a negative impact ($t= 6.246, p < 0.001$) on the dependent variable. All the goals that were adjusted were done so upward. This means that when the daily goal was increased, the participant had a higher and harder goal to reach. By increasing the goal, the change had a negative impact on the likelihood that the user would achieve a higher step performance. Thus, even though changing the goal is a type of engagement, it is not a positive influence, which suggests that there might be other reasons behind this result.

Additionally, the incorporation of notifications ($-3.812, p < 0.001$) was associated with a negative influence on the step performance. This suggests that the more notifications the participant was exposed to, the more negative impact it had on the step performance. The notifications were hypothesized to have a positive influence because it reminded the user to perform a task, such as attaining the step goal. However, the finding could indicate that the notifications stress the user, who subsequently ignores them.

These findings are further explored by discussing the participants' perceptions in the sections below.

5.8.2 Sleep performance results

The dependent variable is calculated as the sleep performance. Similarly to the step performance, the sleep performance is a measure of the rate of the performance in relation to the goal. The dependent variable is:

$$\text{Sleep performance} = 1 + \frac{(\text{sleep goal} - \text{sleep result})}{\text{sleep goal}}$$

Based on the data collection and the hypotheses, the proposed model is:

$$Sleep\ performance = b_0 + b_1\ dsl + b_2\ bed + b_3\ app - b_3\ cg + b_4\ not + b_5\ soc$$

The regression model indicates that the $r^2=$ is 0.48 and the adjusted $r^2=$ 0.47, which means that around 46.8% of the variance may be explained by the independent variables.

Variable	B	Std. Error	Beta	t	Sig.
Constant	.417	.028		14.683	.000
Deep sleep (DSL)	.137	.006	.664	23.066	.000
BedtimeBF23 (BDT)	.088	.019	.137	4.585	.000
Social connections (SOC)	.037	.017	.063	2.149	.032
Times app checked (APP)	-.008	.004	-.062	-2.085	.037
Notifications (NOT)	.013	.009	.041	1.369	.172
Changed goals (CG)	.008	.025	.009	.299	.765

Table 17. The results of the regression analysis of the sleep performance.

The results suggest that four of the independent variables are significant, whereas two are not. Hypotheses 2, 3 and 11 regarding deep sleep, bedtime before 23.00, and social connections are accepted. However, hypotheses 7 and 9 regarding notifications and changed goals being associated with the step performance are rejected. Moreover, hypothesis 5, the number of times that the app was checked, was associated with a negative influence on the sleep performance, which indicates that the hypothesis must be rejected. However, hypothesis 5 still indicated to have a significant influence on the sleep performance. Therefore, the results assume the following model:

$$Sleep\ performance = 0.417 + 0.137\times dsl + 0.088\times bdt + 0.037\times soc - 0.008\times app$$

According to the results, the hours of deep sleep were the strongest predictor (0.137, $p < 0.001$). The measure of deep sleep is a representation of the sleeping activity itself, and means that an increase of the amount of deep sleep predicts a

higher sleep performance. Secondly, adopting the habit of going to bed before 23.00 also showed significance (0.088, $p < 0.001$). The third and last predictor was social connections (0.037, $p < 0.05$). Although the hypothesis 5 was rejected, it is still included in the model as checking the app was significant (-0.008, $p < 0.05$).

The strongest variance was found in deep sleep ($t = 23.07$, $p < 0.001$), then bedtime before 23.00 ($t = 4.59$, $p < 0.001$) and lastly social connections ($t = 2.15$, $\text{sig} < 0.05$). These findings indicate that the sleep performance was primarily predicted by the performance of the sleep activity, such as getting deep sleep. However, it was also positively predicted by the behavior of the individual, for example, going to bed earlier than 23.00. Lastly, social connections also influenced the sleep performance, which might mean that the exposure to other self-tracking users' data on sleep has an effect on a user's behavior.

However, engagement through notifications and changing goals did not have a significant influence on sleep performance. The participants in the study rarely changed the goals when it came to sleep, which suggests that there might not be sufficient data to explore whether this had an impact. The notifications might be useful for awareness, but are not able to influence actual performance, as sleep is an unconscious state. This is in difference to steps, where the user can actively choose to walk for a longer duration.

The findings of the regression model analysis are valuable because they give insight on how the participant's behavior influences the step performance and sleep performance. However, these findings also indicate that the engagement category was associated strongly with step performance. Yet, when it came to sleep performance, engagement was less influential. Nevertheless, checking the mobile app is a predictor of both steps and sleep despite the different types of influence. Moreover, social connections are also positively associated with both models. This indicates that including social functionalities does have an impact on the measured performance. Beyond the functionalities of the device, the actual behavior of the participants had a notable influence on the step and sleep performance. This is unsurprising, since it takes participation in the lived experience in order for the technology to capture the data.

These findings cannot predict or present the perceptions or experiences that the participant gained while being exposed to the data, but only illustrate the experience embodied by the device. The findings open up a number of concerns regarding the similarities and differences between these goals. Therefore, the post-study-interviews are a valuable resource for exploring how the participants engaged and perceived the self-tracking in relation to engagement, social connections and behavior.

5.9 Participant perception on engagement with the data

This section extends the above findings by including the user's perceptive on engagement and interaction with the mobile app that presented the personal data. The level of engagement with the device and data is important to understand its relationship to personal performance, and this is extended by including the perceptions that arose from the engagement. For the purposes of this study, three types of engagement with personal data were measured with the help of the RescueTime software. These are the number of times the app was checked per day, inclusion of social connections, and changing the goals and notifications.

5.9.1 Checking the app

The engagement with the personal performance data occurs through the Jawbone UP app as a departure point. An ideal process of engagement would be that the participant is engaged with his or her data by syncing and uploading the data, followed by viewing the results and utilizing the features, some analytical and some social. However, as mentioned previously, engagement includes participation through viewing the data as well as interaction through using features of the app. Of interest is the fact that the level of interaction is not possible to measure through RescueTime, yet it is possible to measure the number of times that the app was opened. It was evident in the study that the males checked the personal data with a mean of 2.2 times per day, which is more than females who only checked on average 1.7 times a day. Overall, the participants checked an average of 1.95 times per day.

The overall engagement with the mobile app changed over time, both in terms of steps and sleep. From the start, the participants were eager to know more about personal performance and engagement was frequent throughout each day. Several

participants claimed to “*check it very often*” (QSO14, 23, male) and “*After a while, about a week, it became very natural to have it on, and to check it in the evening*” (QSN10, 24, male). However, no participants mentioned active time as an interesting measure but primarily referred to the total number of steps. The engagement primarily started in the morning when the mobile app would be synced and checked to view the sleep data. One participant said “*I was mostly interested in monitoring my sleep, so I usually checked that in the morning after I had woken up*” (QSO9, 22, male). Another participant expanded that “*I checked my sleeping activity in the morning, just to see how much I had slept. But the other stuff I just checked in the evening*” (QSO5, 23, male). The step data was therefore “*checked during my lunch break and then at night*” (QSO10, 29, female). After a while, the participants would not check the app as frequently: “*In the beginning I checked three times a day, but lately it has only been once a day*” (QSO2, 23, female). Another participant explained why the frequency dropped: “*In the beginning I checked it all the time, it was something new and exciting, but then when I got my average it wasn’t so interesting anymore, more a routine*” (QSO6, 25, male). These findings suggest that after the initial week of self-tracking, the participant had the perception that he or she had an understanding of the personal performance and therefore started checking the mobile app less because it was not necessary. The curiosity had decreased. A participant described the overall experience: “*I was so excited about it in the beginning because it was a new device for me, and after a while I got used to it and stopped caring so much. I think my motivation for monitoring and reaching my goal decreased as I got less interested in the technology itself*” (QSN14, 23, male).

When it came to sleep related performance for some of the participants, checking the app had a negative influence on the sleep performance. One participant explained that she “*felt it was controlling in the sense that I felt the need to check it as soon as I woke up. And it had an effect on my consciousness. I didn’t think about how much I slept before*” (QSN9, 22, female). Another participant agreed, because he had started to track how long it took to fall asleep and he noticed it took “*up to one hour, which was extremely frustrating*” and impacted the engagement with the app because “*tracking the sleep had much more impact on my daily life than step activity*” (QSN7, 23, male). One participant plainly stated that the personal data led to the response that “*I know I sleep too little and that it’s affecting me*” (QSO15, 23, male). These experiences might be representative of

the regression model result that indicated checking the app had a negative influence on sleep performance. The data about sleep might create an effect of powerlessness on the participant, who feels that little or nothing can be done about the performance. This is in difference to the step data, where the participant consciously knew that it was possible to go for a walk to acquire more daily steps.

On the other hand, in another discussion, checking the sleep data indicated that the deep sleep measure was interesting to several participants and served as benchmark for the quality of sleep. For example, one participant said that he had fulfilled the sleep goal but felt that deep sleep was a success criteria in the sleep department by stating that *“I could clearly notice that I was more tired on those days where it said that I had woken up a few times during the night, compared to those nights where half of the time had been deep sleep and the other half light sleep”* (QSO1, 29, female).

5.9.2 Changing the goals

The regression model analysis indicated that when the goal was changed it had a negative influence on step performance. However, changing the goal had no significant association with sleep performance. Due to the impact on step performance, this was discussed during the post-study-interviews to gain understanding of the perceptions versus performance. The Jawbone UP goal for step can be changed at any time by the participant by logging in to the mobile app. Despite this option, many of the participants kept the same goal throughout the study period, meaning that the goal was not adjusted upward or downward. Instead, 86.9% participants chose to keep the goals that they had entered in the beginning. Those that did change goals included 12.6% of the females and 13.4% of the males. In all instances the goal was increased.

If the goal was changed, it was primarily steps, while the sleep goal mostly remained the same for all participants. A participant shared this: *“I started out with 4,000 but realized that it was too little so I changed to 6,000 steps instead, and I mostly exceeded it”* (QSO7, 23, male). However, most commonly the participants stayed with the goal that they had originally set upon installation. A participant said that *“I had set it to 10 000 steps and 8 hours of sleep as my daily*

goal. [Jawbone] suggested that I raised my activity goal, but I felt that what it suggested was a tad too much so I never changed it, because if I hadn't reached that new goal I'd just have been annoyed" (QSO8, 30, female). Another participant shared that "I never considered changing them [...] Even if I didn't reach my goal I saw it as a motivator" (QSO15, 23, male). These participants refrained from changing the goals and preferred to remain with the goal that they had initially indicated in the app. Even if these participants did not reach the daily goal, they often chose to maintain the same goal because "I realized that I don't walk 10,000 steps on a day, I only reached that 4 or 5 times" (QSN2, 24, female). Even if the participants did not reach the daily goal, they did not consider adjusting it either upward or downward.

5.9.3 Notifications

Notifications had a negative influence on the participant's step performance, yet it did not have any significance in relation to the sleep performance. The notifications come in various formats by addressing sleep or step data gathered based on the behavior of the participant. The notifications are mainly customized and sent based on the participant's performance. For example, a notification may be that the participant has been idle (not active) for a certain amount of time. The participant can choose to specify the time span, for example, 60 minutes. If the participant has not moved in 60 minutes, the Jawbone UP sends a notification. Alternatively, the participant is sent a notification that it is time to go to bed in order to reach the sleep goal. A participant that performs well in relationship to the goals may never receive any notifications, even though they are turned on. All notifications can be individually turned on and off at any time by the participant. As the notifications have proven to influence step performance, this is elaborated below with participant perceptions.

The participants primarily underlined that the notifications signaled awareness that encouraged movement. One participant said "[I] think it was a good reminder to get up"(QSN4, 23, female) and another agreed that "I sit still most of the time, so I used it as a little reminder, then I would get up and move" (QSO14, 23, male). Some participants described that the notification was not only about moving, but to take a break without moving: "I used it more as a pause alert if I was studying"(QSO12, 25, male). Another participant indicated that the notifications

did not only necessarily influence behavior instantly, but could also have an effect on future behavior. He said *“I got these notifications if I had been active or not during the day, and tried to do better the next day, instead”* (QSN5, 23, female).

However, sometimes the notifications came during times when the participant could not do anything, which resulted in ignoring it. For example, one participant said that *“if you’re working on a project or sitting in class you really don’t want to get up”* (QSO10, 29, female). Another shared that *“it would buzz when I was in class. If I were at home, I’d get up and go to the kitchen for a glass of water or something. But during lectures, I couldn’t really do much!”* (QSO11, 26, male). The habit of ignoring the notification seemed to develop over time. A participant said that *“I took big use of the idle alert for about three days: I went up, I stretched and so on, but after those three days that diminishing effect started and if I was in the middle of something then I forgot to get up and take that stretch break”* (QSO15, 23, male).

The notifications were considered to be useful to signal awareness as a departure point. However, over time, the participants began to ignore them, especially in circumstances where they argued it was not possible to be active. The negative effect displayed in the linear regression might be a signal that the participants started to ignore the notifications, or even felt that they were intrusive because *“it just gets annoying and a little needy”* (QSO10, 29, female).

5.10 Participant perception on social connections

Social activity and online networking was another type of possible engagement with the personal performance data. The Jawbone UP app has a feature that enables the possibility to add other Jawbone UP users. If users are added, it is possible to share personal data as well as take part in one another’s data. In this field study, 24.5% of the participants added one other user. One participant shared that *“I thought it was an interesting feature to be able to compare data with other people, but I didn’t know of anyone else that was using it”* (QSN17, 28, male). The main reason was because the participant did not know others that were using the self-tracking device and therefore did not have the possibility to utilize these aspects. While many participants had a positive reaction to the idea, a select few thought a social feature was unnecessary: *“I wouldn’t be interested in taking part*

of other people's' results or sharing my own. It feels pointless and a bit private" (QSO2, 23, female). Those opposed to social inclusion were mainly hesitant because of privacy concerns.

Even though the social feature was not used, several participants were positively inclined toward it and reflected on its impact on the experience. For example, one participant thought *"If I had social connections I'd definitely compare myself with them, as I'm extremely competitive as a person"* (QSO14, 23, male). Another concurred and added, *"I would pay some attention to people's data, especially sleep data. I guess you get kind of competitive, which could be cool"* (QSO9, 22, male). Yet competition was not always the main reason to get social connections. Participants also wanted them because of comparison and community: *"It's so much more fun if you have someone to compare yourself with, instead of just being on your own with your results"* (QSO17, 24, female). Since so many did not have the possibility of sharing perceptions and experiences about the data on the app, several chose to discuss the device and related personal data outside a digital context. Participants generally saw it as a positive experience and that *"A lot of people asked about it"* (QSO15, 23, male) and *"People were in general very interested in the device itself and wanted to look at my diagrams and asked if they could see how I'd slept and so on. It was a good conversation starter!"* (QSO16, 23, female). Even more so, participants would talk to others because *"it's kind of a benchmark"* (QSO6, 25, male) on which they can make comparisons.

According to the linear regression analysis predicting the step performance, even a minor influence from social connections had a significant influence on the step performance. The participant's reflections on social connections in the self-tracking app suggests that they were primarily positively inclined to having social connections and would have utilized this function more, if it was possible. The primary reason for not having social connections was due to the lack of knowing others with the same device. The social features were considered something that was likely to inspire more engagement because this would bring in opportunities to compete, compare and share different aspects of the self. However, the few that frowned upon the idea thought that it was too personal and irrelevant data for others to share in.

5.11 Participant's perception on behavior

The participant's behavior, namely the personal performance, was captured and embodied by the experiential device. The linear regression analysis indicated that the measurements of the performance were positively associated with the step performance. For steps, active time was a predictor, while for sleep, deep sleep and bedtime were predictors.

Beyond the measured performance, the participants were also asked about the perceptions of the behavior when using the Jawbone UP. Most predominantly during the post-study interviews, the exposure and interaction with performance data was argued to lead to awareness and insights by the study participants. The engagement with the data led to awareness about habits surrounding the performance measurements, such as insight on behavior related to sleep and step.

This section proceeds to discuss the perceptions of the participants on the behavior and related experiences that they had with the performance data. During these conversations and the analysis of them, it surfaced that there is a perceived objectivity of the data that is seemingly led by subjectivity. The exercise of reflecting on the self due to the exposure of data introduced a complex process.

5.11.1 Behavioral change

Both the step and sleep performance was positively associated with behavioral variables. More specifically, the step performance was associated positively with active time while sleep was positively associated with deep sleep and going to bed before 23.00.

The active time was positively associated with step performance, which indicates that the more active the participant was, the more likely the greater step performance. The behavior of the participants changed and many attempted to be more active, knowing they were wearing a Jawbone UP. One participant said *"I often went out for extra walks just to compete with myself - having this device made me think that I should be more active"* (QSN7, 23, male). Another agreed and said that *"I tried to push myself more on those days when I didn't have anything planned, and made sure to go to the gym with friends. So yeah, I became more active"* (QSN14, 23, male).

In terms of attempting to reach the goal, the participants sometimes adjusted the bedtime to an earlier hour. One participant would *“make sure to go to bed at a decent time so I could reach the 6-8 hours, I felt more encouraged to reach my sleeping goal”* (QSN14, 23, male). Another agreed and said *“I’d go to bed at a good time, even if I wasn’t tired yet, just to try to reach those 6-8 hours of sleep”* (QSN10, 23, male). However, the considerations around deep sleep were not equally common, beyond the fact that the participants would check the data. One participant said *“I could see how much I had slept and how much deep sleep I’d had, but it didn’t change anything for me”* (QSN16, 23, female). However, those who spent a little more time on tracking the deep sleep got more insight from it. In other words, the deep sleep data was checked and brought awareness and even insight, but did not necessarily create any behavioral change.

Overall, the awareness about personal performance seemed to boost the participants’ perception about adopting behavioral change, both in terms of steps and sleep. Several participants perceived that they had made changes to their daily routines after being exposed to personal performance data. However, the behavior change did not necessarily occur. One participant described that the changes *“just turned into a really nice habit”* (QSO8, 29, female) and then elaborated: *“I’ve tried to change some of my routines in order to reach my sleep goal, like tried to plan when I have to get out and walk the dog for the night”* (ibid). This was supported by another participant who became more rigorous about keeping active routines *“Even if the weather was bad and it was tempting to take the metro, I would often chose my bike to get my activity data up”* (QSO11, 26, male). Other behavioral changes were less planned and more sporadic, such as this participant, who said that *“I often went out for extra walks just to compete with myself. Having this device made me think that I should be more active”* (QSN14, 23, male). The awareness had a particularly positive impact on a participant who said: *“it has changed the relationship I have to my body. I prioritize food, sleep and activity much more [...] For instance, I always choose stairs instead of elevators now, which I never did before, and I try to drag my friends with me at the same time”* (QSO2, 22, female). The aspiration to change was apparent in the discussion, even though the daily goals were not attained. For example, one participant shared that *“I had a goal set, and even though I never reached my sleep goal I got very aware*

about my activity and the goal I had set for that. I feel that I need to stand up, walk more, and so on" (QSO4, 27, male).

When it came to sleep and behavioral change, the participants felt it was difficult to directly impact the sleep performance, so they focused on changing the premises for going to sleep, such as altering bedtimes. One participant proudly shared that *"I managed to get my average hours of sleep up from 1.5 hours to 8 hours. I used to forget about time before and got lost into work very easily, but with the Jawbone I got more aware of when I had to go to bed"* (QSO15, 23, male). Another participant said that tracking the time it took to fall asleep influenced him to even change his activities prior to bedtime. He said *"Since it took such a long time for me to fall asleep, I started doing calming things before going to bed, such as reading a book instead of watching tv"* (QSN7, 23, male). One even considered altering sleep by minimizing it because *"I found out that I sleep extremely light the two very last hours every night, so I'm considering sleeping one hour less no as I don't get any use of it"* (QSO7, 23, male). The habits surrounding sleep were thus scrutinized by the participants who perceived that making changes had positive effects on their performance.

On the other hand, some were under the perception that behavioral change did not occur after having being exposed to personal data. The perception was that the participant did become more aware but without making any changes to behavior. One participant shared that *"I think it was very interesting to see how I'd slept, as the data often showed me that I had slept worse than I thought, but it didn't make me sleep better"* (QSN11, 23, male). Another shared that *"It was very interesting to see, of course, but I never felt encouraged to do more"* (QSO9, 23, female). Some even attempted to change behavior but it did not work in the long term. For example, one participant said that *"I tried to go to bed earlier, at 10 pm, but it was just way too early for me so it didn't work"* (QSO6, 24, male). Overall, it may not have *"changed anything, but maybe my mindset in general"* (QSO14, 23, male).

The underlying reason for not changing behavior might be that the participants did not know how to utilize or adapt the data and turn it into actionable insights. A common argument was that the participants did not know what the data meant and what to compare it to. Several of the participants that voiced these concerns are similar to those that did not perceive that they gained any insight. For example, *"I*

was never sure if I had performed well or not and if my result was normal" (QSN10, 24, male) and that "I don't know what to do about the information" (QSO3, 23, male). One participant interested in sleep stated "*I expected that it would help me more with my sleep. Of course, I could see how much I had slept and how much deep sleep I'd had, but it didn't change anything for me*" (QSN16, 23, female). In this light, the expectations of the self-tracking activities seemed to be that insight would be automatically delivered device and understood by its receiver. However, in several instances, the participants did not perceive that they gained awareness or insights. A suggestion was that "*It would've been cool if it had shown you more specific reasons for your results, like why you slept bad was because you went out partying*" (QSN16, 23, female). But in the end, several participants simply voiced that "*I thought it would do more for me, so I was a bit disappointing*" (QSO3, 23, male).

5.11.2 Awareness and insight

The interviews unraveled that the participants gained awareness around their own step and sleep performance on a daily basis. The increased awareness indicated that the participants were curious about reviewing the data, but also remained reflective as well as critical towards the validity of the data. Participants would typically voice that "*the more numbers and data I got out of it, the more aware I got*" (QSO8, 29, female) and "*you get to know yourself more, how active you are and how much you sleep. It just makes you more aware*" (QSN7, 24, male). The participants thus increased awareness about the self and personal performance by being exposed to the data. The data was perceived as deeply personal, as one participant described it: "*this data shows how much I care for myself, and helps me to be more conscious. I think my generation doesn't have 'stable' lives filled with routines, so it's good to get this data and pin down what you're actually doing and not doing*" (QSO16, 23, female). It helped the participant to get an overview of a hectic life and created a type of self-reflection through data. The outcome of self-tracking practices was also described as that "*the data was like a diary written by my body*" (QSO2, 23, female). The data thus gave a new way to look at themselves and that "*data is something that has been processed to clarify things for me, so I can see patterns and results. It's my life, but simplified*" (QSN16, 23, female).

Beyond immediate awareness about personal performance, some participants started looking for further insights by analyzing, comparing and experimenting with the data. One participant stated that *“I started to track how much time it took for me to fall asleep, and sometimes I and up to one hour which was extremely frustrating”* (QSN7, 23, male). Another participant found *“a clear pattern if I had slept at my girlfriend’s place or not. She moves around a lot and it seems to disturb my sleep because I sleep data was much better if I’d slept alone”* (QSO3, 23, male). A third participant also monitored the sleep data and said that he *“had slept for 8 hours but still felt exhausted when I woke up, but then I saw that 6 of those 8 hours had been light sleep, and that explained why I was so tired”* (QSO15, 23, male). The insights brought light to how different experiences were associated and actions interrelated, such as the importance of deep sleep during a sleep cycle. Further analysis also occurred in relation to steps. One participant explained that the *“most interesting day was definitely the day I was sick in bed all day and only got 70 steps”* (QSN12, 25, male). Another participant said that he visited and explored another city, Malmö, and *“I had reached my goal with 180%”* but also that *“then I had days when I didn’t move much at all but went to salsa dancing - and I ended up with the same result as when I went to Malmö”* (QSO11, 26, male). In these examples, both participants got an understanding of very high and very low movement patterns. Overall, some of the participants went beyond immediate awareness and proceeded to evaluate the data for further insight and draw conclusions based on the data, despite the outcome.

Nevertheless, there were instances where some participants argued that the self-tracking practices were needless because they already had a sense of self-awareness: *“I often knew myself I’d had a bad night’s sleep. I didn’t need the Jawbone to tell me that I had only slept for 3 hours!”* (QSN12, 25, male). Another similarly claimed that *“it didn’t tell me anything new”* (QSN16, 23, female) because she already had an idea of how active she was. Both these participants thought that the data collected was self-explanatory, and at times trivial, thus preferred to rely on instinct, instead. Sometimes in such instances, the participants were frustrated about the lack of insight and pointed towards the actual device as having too few features and functionalities to allow the participants full insight into themselves. For example, *“I had quite high expectations and thought it would do a lot for me, but it had less features than I expected”* (QSO3, 23, male).

5.11.3 Changes in perceptions of the data

The participants' perception of the data changed over the duration of the study. In the beginning, participants mainly perceived the data as trustworthy, whereas once the study was underway, this perception was magnified or demoted. The change in perception was often due to the level of trust that participant perceived of the personal data. Some participants had a strong trust for the data throughout the study, whilst others lost it along the way, and some never had it to begin with. The participants were asked about trust for the step and sleep data on a 7-point Likert scale at the end of the study. The results indicated that the trust was fairly high, despite a great deal of critical claims regarding trust. The trust for sleep had a mean of 5.4, whereas steps had 5.3. A total of 63.2% rated the trust for sleep 6 or above, which means that they found it "very to extremely trustworthy". When it came to steps, there was some more hesitation, so 54.1% rated the steps "very to extremely trustworthy". None of the participants rated a trust lower than 2. In light of these differences, the quotes below describe participants who had various views on trust. One particularly critical participant exclaimed "*I'm a bit critical towards data, since it's usually made by someone else, and then when it says that it's supposed to reflect something specific I cannot trust it completely*" (QSN9, 23, female). On the other side, one positive and trusting participant said "*You cannot fool the device, so that was cool for me to see*" (QSO14, 23, male)—he was indicating the device was trustworthy in gathering and translating the performance data.

The main point of critique for the data was the level of accuracy by which the self-tracking device monitored the participant. If the participant perceived the device as inaccurate in its measurement, the participant argued that it had a direct effect on the trust and motivation to continue use. The distrust often stemmed from personal experiences or considerations. For example, one participant said that "*I couldn't trust the data. One night I got out of bed and walked around in my apartment for a bit, but Jawbone didn't detect that I was up and awake*" (QSN12, 25, male). The participant thus tested the device that failed to deliver according to the expectations. Such an occurrence might lead to a situation in which the participant stops logging sleep and only tracks steps instead. However, despite some critique of the device, the participants thought it was useful to get an overview of personal performance. One participant argued that "*I think we all agreed that it wasn't as*

accurate as it could be, but overall I trust it and think that it shows the tendency of my sleep and activities” (QSN11, 22, male).

Social connections also had an influence on the participant perception of using the device. One experience had a negative impact on the self-tracking and this impacted the participant’s perception. As a result, he started using the data less: *“I was very enthusiastic in the beginning and checked it very often. Then I got very influenced by some other friends that were also using Jawbone, who told me that it doesn’t measure precise [...] After that I used it less and less”* (QSN11, 23, male). The participant’s perception of the data was influenced by others and caused a decline in the usage. On the other hand, social connections could also create the opposite effect where a positive perception was increased. For example, one participant was encouraged to speak to others because *“it’s kind of a benchmark”* (QSO6, 25, male) and that it brings a sense of community where *“that you can chit-chat together”* (QSO17, 24, female) about results.

5.11.4 Continued use and engagement

After the study, each participant was asked whether she or he would continue the use and engage with a self-tracking device if possible. 73% of the participants answered that they would continue using the device. The participants who said that they would not consider continued use said *“It was nice to try it, but I wouldn’t buy it. It wouldn’t make a positive change in my life”* (QSN09, 23, female). This participant had particular concerns about the sense of control that wearing such a device would exert. Alternatively, another participant found this control aspect particularly appealing by stating *“I feel that I should buy one, so I have more control of my activity”* (QSO4, 27, male). On the other hand, those that wanted to continue using the device stated that it had positive impact on awareness. One participant said *“I want to buy bracelets for my family! People should be more aware of their physical health”* (QSO2, 22, female). Several participants voiced that they would continue using the device, but wanted more features: *“Yes, definitely. Especially if its features evolve”* (QSO3, 23, male) and *“I would definitely continue using this device if it evolves a bit, as I’m missing some features, such as “measuring stress”(QSO4, 27, male) or “blood pressure measuring”(QSO6, 25, male) or “measuring my pulse, because I think that says more about your general health”(QSO12, 25, male). A few wanted to continue using such a device, but only “if it was a bit less expensive”* (QSO5, 23, male).

5.12 Towards an understanding of perceptions of self-tracking practices

The study on new self-tracking practitioners gave an understanding and overview of the first few weeks of engaging in self-tracking through an activity tracker. The brief study allowed the analysis of what factors influence performance while activity tracking as well as gaining perspectives on this practice. In summary, the regression model showed that step performance was influenced by physical performance but also through engagement with the data through the app. The sleep performance also indicated that physical performance and engagement with the data led to better results. The engagement with the personal data led the participants to generally perceive a heightened awareness and sometimes also gain deeper insights. The spillover effect of engagement and awareness often led to behavioral changes, both sporadic and routinized ones. However, the perception of the data changed over time due to a wide variety of factors, which could not be fully captured in this study. As a result, several questions arose in relation to the findings, such as how awareness and behavioral changes are maintained, adapted or extended over time. On the basis of these queries, the inclination to conduct a study with experienced users appeared. The reasoning of these queries is elaborated below.

The participant reflections are often related to awareness, but less so about in-depth insights or analytical processing of the data. As the study was conducted in relation to new self-tracking users, it would be interesting to explore whether the immediate awareness of performance might be a result of novelty or persists over a longer period of time. There is a possibility that the long-term user had already passed a stage of awareness and addresses the daily data accumulation in a different way, such as analyzing data for deeper knowledge.

The reluctance to change the goal might also be related to the shorter duration of self-tracking activities. The goal-setting mechanism is a central part of the mobile app as well as the user experience because all of the data is placed in comparison to this goal, which in turn influences the user. Still, the participants refrained from changing the goal and commonly adhered to the context that they had been placed in. The reluctance to change the goal might be because the duration was too short and therefore the participants did not make adequate adjustments. The perceptions

around goal setting would also be interesting to explore as a way to better understand the perception of self and personal performance.

The perception of adopting behavioral change as a result of exposure to personal data was prominent in the post-study-interviews. The behavior that changed was primarily an attempt to improve the personal performance. When it came to steps, the participants described that the behavior change would be to increase the performance measurements (e.g., better step results) by going for extra walks or going to the gym. However, when it came to sleep, the participants would change the habits surrounding the sleep, such as going to bed earlier, doing calming things before bedtime, and tracking disturbances followed by excluding them. Nevertheless, the study only tracked self-tracking users for the duration of a month or less, which only shows the behavioral changes that occurred in the initial phase of adoption. Even during the month, participants expressed that the “*motivation for monitoring and reaching my goal decreased*” (QSN14, 23, male). Therefore, it would be interesting to discuss the perceptions of awareness, behavior and related goals with users who have engaged in self-tracking for a longer period of time.

Lastly, the users of this study were not experienced users in the sense that they had individually and personally pursued a self-tracking device. By conducting another study with experienced users who have independently chosen to engage in self-tracking, the perspective on the data, outcome and behavior might offer alternative angles and appreciation of the experience between technology and user.

Based on findings of this study of new self-tracking users, the subsequent study in the next chapter seeks to develop an understanding of how individuals who are long-term users perceive the self-tracking experience.

5.13 Limitations

The field study was not without limitations. A first learning lesson from implementing this research design is certainly that it is extremely time-consuming. The study required a number of steps from beginning to end. This proved to be a process that required about two to three hours to be spent on each participant. The recruitment process was brief, since it merely involved a presentation. The second step was to contact the participants and set up a time for a one-to-one meeting, yet

40% of these were rescheduled due to failure to appear by the potential participant. Some revisited while some did not. The next step was the introductory meeting, which took about 30 minutes per person because it involved going through the agreement, allocating an anonymous identity, installing and activating two mobile apps, and activating the survey schedule. The last step was to schedule a post-study-interview that took another 30 minutes. The time-consuming research design lead to limitations in the number of times it was possible to conduct the study.

The study primarily involved human behavior, such as step and sleep performance, which is a relatively unreliable source of data, as human nature is inconsistent in itself. This means that the participants may have a really wide range, especially when it comes to steps, as they may move very little or a lot from one day to another. This in turn creates the discussion regarding potential outliers, which the linear regression model is sensitive to. In order to check for this limitation, the data was reviewed for any extremes, which led to the omission of one participant, since this person was training for a marathon, but who also moved very little on days where running was not scheduled.

The study was conducted from October to November 2014. The participants may have been more or less active if the study was conducted in a different time of the year. For example, during summer the participants may have been more active as the weather generally allows more outdoor activities. Furthermore, the end of the year might mark the end of courses at university, which means that some may have spent more time in a sedentary position due to projects and coursework.

Moreover, the participants of the study were students of the Copenhagen Business School. The daily pattern of a student may be different from those working full time and is likely to be less routinized when it comes to both steps and sleep.

Another limitation is that it is difficult to define the participant's previous and general knowledge of self-tracking and wearable technology, which might in turn have impact on how the activity of self-tracking is performed and perceived. While it was a prerequisite that the participant should not have engaged in self-tracking before, they may have read and heard about the practices, which in turn influences the experience.

The device brought on some limitations as well. In this study, several of the devices broke during the study. Some participants decided to ask for a replacement, some did not notice that the device was exposing irregular data, while others attempted to fix the device themselves. This resulted in irregular data collection that eventually led to omitting some participants from the study. Moreover, the Jawbone UP comes in three different sizes and in all the study rounds, there were not enough devices for the most requested size. It was not possible to wear a smaller or larger size due to the discomfort as well inaccurate reading. For example, 15 people signed up for a size medium but there were only 10 medium wristbands available. Study expenditures were also limited so despite the interest, it was not possible to purchase more devices. This means that the people were assigned for the next study session but often they did not reply back upon re-initiated contact.

5.14 Chapter summary

This chapter introduced the first study of new self-tracking users. The first study is a field study that involves primarily quantitative data with qualitative post-study-interview data as well. The study commenced with a pilot study that informed the full scale study. The final field study had 34 participants and 849 observations on step, sleep and interaction activity. The study collected both physical performance data and perception data, which were based on interviews with the participants. The study provided evidence regarding the step and sleep performance and perception of new self-tracking users. In the quest to explore this research topic, this study served to validate some of the themes and questions that inspired and formed the interview guide of the second study.

6. STUDY 2: EXPERIENCED USERS

6.1 Introduction

The second study consists of 54 in-depth semi-structured interviews with purposive sample of self-tracking individuals who were using devices Jawbone UP or Fitbit Flex. The study asked “How do users experience the practice of self-tracking for the purposes of motivation and behavior?” The interviews were transcribed, imported and coded in the software MaxQDA. The coding and analysis was conducted through a thematic analysis.

The research area is focused on specifically addressing experienced users of self-tracking devices, in comparison to the previous study that reviewed completely new users. The aim is to gain further understanding of the experiences and perceptions of these experienced users, exploring them through in-depth interviews to collect empirical data about an emerging research area. The exploration is needed to get insights on new aspects (Bloor, 2001), which might differ from that of new users.. Therefore, many similar themes are addressed in the interviews, such as motivation, perception, experiences and expectations as they differ over time. These interviews present a possibility to further refine the understanding of how the self-tracking user evolves from a new user to an experienced user, and the variations in experience that lie between. It also serves to reinforce the continued building of a richer discussion that will serve future studies.

The semi-structured interviews allowed further insight into the research topic by examining at how personal data influences users when they interact with a specific device and app that rests primarily on personal data.

The below table gives an overview of the study that are introduced in further depth below.

Study 2 Overview	
Study type	Qualitative
Sample	54 interviewees
Method	Semi-structured in-depth interviews
Data	One-to-one telephone interviews
Research question	How do experienced users experience and perceive the practice of self-tracking in terms of personal performance?
Gender distribution	30M 24W
Analysis	Qualitative analysis through thematic analysis
Software	MaxQDA

Table 18. Overview of study 2

This section presents the empirical investigation done by interviews and presents an elaboration on the overall chosen method, sample and procedure followed by analysis method. This is followed by the study's findings.

6.2 Sample, recruitment and procedure

The sample is 54 telephone interviews that were gathered as a purposive sample. The sample consists of 30 men and 24 women between ages 20-50. Interviews were conducted in Swedish, Danish or English. All interviews were anonymous, audio-recorded and transcribed verbatim and at full length. The interviews are between 25-50 minutes long. This translates into approximately 420 pages of transcription. The interviewees mainly resided in European countries, more specifically Denmark, Sweden, Germany, UK, Ireland or Finland. The remaining interviewees lived in North America. The self-tracking culture and Quantified Self community is more dispersed in North America and Europe (Quantified Self, 2011).

The below table illustrates an overview of the sample interviewed.

	Jawbone UP	Fitbit
Number of interviews	42	12
Gender Men Women	25M 17W	5M 7W
Age 20-30 30-40 40-50 50+	27 9 5 1	8 2 2 0
Occupation Student Academic White-collar Blue-collar	4 5 30 3	2 3 5 2
Location Europe N. America Asia	36 4 2	10 2 0

Table 19. Demographics of the study 2 participants.

The recruitment took place in several different settings, such as online forums, at physical Quantified Self meetup groups, conferences, and also randomly on the street if a self-tracking user was spotted. Participation was anonymous and voluntary. Each interviewee was labeled with a code to ensure that such privacy was in place. For instance, if the user was a Jawbone UP user and the 18th person to be interviewed, then the code was JB18. If the user was a Fitbit user and the 12th person to be interviewed, then the code would be FB12. In the forthcoming findings, the interviewee is labeled like this—JB18 (or) F35, researcher—which indicates the interviewee label, gender and age, followed by occupation.

The telephone interviews were conducted with tools such as Skype and FaceTime Audio as well as regular phone calls. The use of different communication tools made it possible to achieve a richer sample of interviewees, as it allowed corresponding with individuals at various locations and time zones. Although the software sometimes had video functionality available, this was not used during the

interview segment. This was done in order to provide a consistent data collection with only telephone interviews, but also to avoid any extra lagging or disruption that the added processing of video functionality sometimes causes. (Occasionally, the video function was used before or after the interview to greet the interviewee and exchange a few friendly words.)

A purposive sample was necessary because it was the intention to interview individuals with predetermined criteria (Cozby & Bates, 2012, p.140). Purposive sampling is particularly popular among the social sciences and can be used for both qualitative and quantitative data collection (Cozby & Bates, 2012; Guarte & Barrios, 2006). It is defined as “randomly selecting units without replacement from the particular section of the population believed to yield samples that will give the best estimate of the population parameter of interest” (Guarte & Barrios, 2006, p.278). The advantage of purposive sampling is that it clearly allows the data collection to target the individuals who are particularly relevant to the research question. However, the disadvantage is that it introduces bias into the sample and results are not generalizable over a population and in fact excludes certain segments of the population (Cozby, 2009; Guarte and Barrios, 2006).

The predetermined criterion for the purposive sample was that the interviewees had to currently be wearing or had previously worn either of the self-tracking devices Jawbone UP or Fitbit Flex. The interviewees were thus chosen based on the fact that they were experienced or self-selected users in that they had made an active choice to wear the device, rather than having this action imposed by an external source. In most cases the interviewees have purchased the units themselves, whereas in a few instances they had received one as a gift, after requesting it. Beyond that, there were no restrictions such as age, gender, or profession. In this data collection process, the disadvantage of such a sample is that it might introduce a bias in which the individuals are very similar since they have actively chosen to pursue self-tracking, which automatically omits the individuals who would not. This suggests that the sample might be a fairly homogenous group of people with similar patterns of behavior and personality. In order to account for this, the studies included in this research project involve individuals who have not worn versus have worn such self-tracking devices.

Each interview was conducted with the help of the interview guide, with categories for discussion: use, goals, experience, motivation, interface, social connections and trust. Each category had two to five pre-formulated questions. At the introduction of the call, the interviewees were introduced briefly to the general interest and focus of the study, followed by the questions. Not all questions were asked of the interviewees, but they served as a guide to cover the categories. At the end, the interviewees were invited to add any extra comments or ask any questions of the interviewer.

6.3 The interview guide

An interview guide was developed on the basis of the empirical findings in the study 1 as well as the findings in the theoretical background chapter. The categories are: use, goals, experience, motivation, interface, social connections, and trust. Many of these categories and attached questions are related to the previous interview guide, but these were expanded as new findings arose alongside the findings of study 1. Both the previous study and the literature review inform the interview guide and were valuable in establishing and assessing the framing of the research. As the study consisted of a semi-structured approach, the interview guide was related to the units of analysis and “designed to guide us, during the interviews’ process” (Mantzana, 2007, p.95). The interview guide leads the investigation of the experienced self-tracking users through the different categories addressed.

The first two categories—Use and Goals—were developed to further understand the general use and application of the device. The questions in the category Use were chosen to understand how an experienced user uses and interacts with the device on a daily level, since this might differ from the new user (Consolvo, Klasnja, et al., 2009; Mimmi Sjöklint et al., 2015). Furthermore, the questions serve as accessible and easy entry points into the interview, and aimed at putting the interviewee at ease. The category Goals is also important because it probes the user’s relationship to the preset goals and establishes an understanding of how these goals are approached, perceived and interacted with. Moreover, goals are an inherent part of the design and use of the self-tracking device, which makes it relevant to address how the user continuously interacts with it. In the former study, the focus was on performance to review experience and subsequent engagement, whereas in this study the focus is shifted to the perception of experience, i.e., of

incorporating these goals into everyday life. These questions hope to encourage the presence of personal narratives as told by the users. On the basis of a greater understanding of the user's use and goals, the interview can then proceed through the next set of categories.

The theoretical background inspired and set down the foundation for the remaining categories: experience, motivation, interface, social, and trust. The categories of Experience and Motivation are closely related, since they focus on the individual's perception of the experience and the influence of the self-tracking device (E. K. Choe et al., 2014). The Experience is a central concept of this research, but also to the users when they are using the experiential devices. This is important because experiential computing asserts that people live within the computing framework, not outside of it (Yoo, 2010). Moreover, the Motivation category was established to better understand the potential impetus that resides before, after and during an experience with self-tracking. This category hopes to shed light on the perceptions regarding any potential incentive, but also on the stimulus for the self-tracking activity.

The Social connections category is related to the social features available in the devices, but was also added because of the importance placed on it in the background literature. Social aspects are relevant to discuss because they can offer a support structure, but also spur comparison and competition among users (Adams et al., 2005; Tajfel, 2010). In light of this, the user might identify or distinguish him or herself from the social data (Hogg, 2000). However, not all users experience social influences during self-tracking, so it is relevant to pose questions about the perception of this because there may be differences in the (lack of) social experience. Moreover, the findings from study 1 indicated that social aspects have a positive influence on both steps and sleep, which suggests that it should be included.

The Interface category is also connected to the theoretical background, which found that visualization and personalization play a major part in the user's experience of the experiential computing (e.g., Bawden & Robinson, 2008; Bentley, Tollmar, & Stephenson, 2013). It is argued that the representation of data needs a stronger conscientious design because it has a major impact on the user's abilities to interact and reflect with the data (Consolvo, McDonald, et al., 2009).

The questions are asked to understand how the user interacted with the interface. It is also a complement to study 1 where it was not possible to track this.

The Trust category is brought forward to further investigate the relationship to the data in terms of transparency and trust, features which, it is argued, increase engagement in the theoretical background chapter (e.g., Jaimes et al., 2013). Trust and transparency is also addressed to examine how the user's relationship to the data and device has evolved, compared to new users.

Study 2 Interview Guide	
Use	How did you first hear about the Jawbone UP bracelet?
	When did you get your first Jawbone UP bracelet? Why?
	How often do you wear your Jawbone UP bracelet?
	How often do you check your Jawbone UP mobile app?
	Describe a regular day with your Jawbone.
Goals	Have you changed any of the daily goals at any time? Why?
	At the end of the day, why do you wear the Jawbone UP bracelet?
Experience	Share a positive experience you have had with Jawbone UP.
	Share a negative experience you have had with Jawbone UP.
	By using a Jawbone, do you experience that behavior changed over time? How?
Motivation	How does it make you feel when you have reached your daily goals?
	How does it make you feel when you have NOT reached your daily goals.
	Describe a situation where Jawbone UP data is relevant.
Interface	When and why do you open the Jawbone UP mobile app?
	What do you look at when you open the Jawbone UP mobile app?
	How do you make sense of the data in the Jawbone UP mobile app?
	What numbers in the app are most interesting to you?
	What numbers in the app are least interesting to you?
Social	Do you have any social connections on the Jawbone UP mobile app? Why?
	Do you pay attention to the other people's uploaded data? Why?
	Do you share your data on other platforms? Why or why not?
	Do you discuss your results with anyone?
Trust	Do you trust the data?
	Do you trust the device?
	What does data mean to you?

Table 20. Study 2 interview guide.

6.4 Thematic analysis

A thematic analysis was conducted by using the software MaxQDA, which provides qualitative and mixed method data analysis (Franzosi, Doyle, & McClelland, 2013). In practical terms, this means that the 54 interviews that had been transcribed into 420 pages of text were saved as Microsoft Word documents and subsequently uploaded to MaxQDA. From these interviews, a total of 1327 snippets were coded into a set of nine categories, which had additional sub-categories. The themes are reactions, behavior, perceptions, expectations, data, trust, social behavior, coping strategies, and interacting with the app. The most used theme was Reactions, with 435 snippets and it has nine sub-themes.

Main themes	Snippets of code	Sub-categories
Reactions	435	9
Behavior	111	0
Perceptions	166	0
Expectations	87	0
Data	33	0
Trust	99	6
Social behavior	73	0
Coping strategies	40	4
Engagement with the app	84	0

Table 21. Overview of main themes of the thematic analysis.

The use of a text-coding program while performing a thematic analysis is considered suitable as well a way to ease the workload (Barry, 1998). By using MaxQDA, the interview analysis gain a working space where it can be

investigated thoroughly by structuring the content by coding text snippets and organizing these in categories. For example, if several interviews mention that self-tracking brought forward awareness about the lack of sleep, these text snippets can be coded and placed under the appropriate category, such as “sleep awareness”. In short, MaxQDA aids in classification and structuring the content of the data, which considerably supports the researcher (Alexa & Zuell, 2000).

6.4.1 The steps of the thematic analysis

The first phase of thematic analysis is to become familiar with the data, or even better yet, to become immersed in the data. Therefore, it is important that the themes for coding are not predetermined when I start to analyze the collected data. However, it should be noted that some categories were already in place during the data collection, since the interview guide contained categories. In order to circumvent re-using the same categories, they must be discarded, since they may no longer be representative of the content of the data collection. However, the thematic analysis started before this, for the process of becoming familiarized with the data began with the interview recording as well as in the transcription stage. In fact, this close involvement gives a thorough understanding and practices analysis and interpretation early on (Braun & Clarke, 2006; Lapadat & Lindsay, 1999). As I conducted and transcribed the interviews, the familiarization was already substantial.

The second phase is to generate initial codes and that should be done once the researcher has gained an idea of the content. Codes are a feature of the data that is meaningful to the phenomenon (Boyatzis, 1998). In this manner, the coding is about details or trends rather than identifying umbrella themes that can be representative of the data collection. The code generation was data-driven rather than theory-driven, so it was generated by exploring the data rather than using a set of theoretical principles or definitions. The coding program, MaxQDA, offers automatic coding instead of requiring the researcher to manually read the documents. For example, the researcher may think that the word “self-tracking device” is relevant to the analysis and therefore performs an automatic search that results in over 50 hits in the text. This approach highlights a specific term, but also overlooks similar or related terms, which is a limitation, and therefore, automatic coding was not used. Another risk while coding is coding fetishism, which means

that the researcher simply codes for the sake of coding, rather than analyzing the content of the data.

A primary round of coding was made and once more than 500 snippets of text had been coded, I could draw the conclusion that it was too superficial and strongly similar to the interview guide. The categorization did not add new insights beyond the initial ones, despite the much richer content retrieved while collecting interview data. This led me to forms the conclusion that it would not provide a nuanced analysis and finally, to dismiss such coding altogether.

In the second attempt of phase two, I shifted the focus from attempting to understand the experience of the device to departing from the user's perspective on the device. With this new perspective, the coding was able to be more focused on representative patterns than on attempts to code the text as a whole. At its peak, the coding had 15 categories and nine subcategories. This was useful for getting an overview, but many of them proved repetitious or too unimportant for the final analysis.

The third phase is searching for themes and refocuses the analysis on a broader level of themes. In this phase, I reviewed the coding to find themes that would logically and accurately place the coding. Based on the 15 coding categories, three were omitted while the remaining 12 were applied for consideration as bigger themes. The coding helped bring forward the evidence that there were surprisingly many text snippets related to what the user was *not* doing and why he or she was not doing it (yet also not doing something else). Reviewing this more carefully revealed that the user applies different types of safety measures and defense mechanisms when discussing personal goal-related performance.

The fourth phase involves reviewing themes and was closely intertwined with the third phase. It was an iterative process where I went back and forth between these phases. This is common because thematic analysis is continuous and the "need for recoding from the data set is to be expected as coding is an ongoing organic process" (Braun and Clark, 2006, p.21). The review of the themes was done by reading the text snippets that had been coded and to examine whether they corresponded to each other and to overarching themes. Once a few themes had been identified, I recognized that I was in need of validation. The interview

transcriptions were sent to two colleagues who reviewed the text and performed a coding themselves. After this had been done, we met for a few hours to discuss the coding, trends and patterns that we had individually identified. The validation procedure was rewarding and allowed three major themes to emerge, while the remaining were left in the background.

The fifth phase is to define and name the themes, as well as understanding the essence of them. The major themes received names, specifically, reaction and coping mechanisms. Beyond the major themes, there were several minor themes that did not hold an equal prominence. These were not dismissed, but emerged as sub-themes to the main themes, instead. The major themes were then re-reviewed to make sure that the related text snippets were relevant and nuanced, yet not too complex and diverse to be unreliable. For example, one major theme was “reactions to goal-related data” and was related to more than 500 text snippets alone. In an attempt to bring clarity to the theme, the snippets were re-coded into seven sub-themes such as reaction to success, reaction to failure, reaction to changes in behavior, and so on. This gives “structure to a particularly large and complex theme, and also for demonstrating the hierarchy of meaning within the data” (Braun and Clark 2006, p.22). This was also done in the remaining themes.

The sixth and final phase is to write a detailed report on the themes. This is done in the Chapter 7.

6.5 The Interview Study: Perceptions of Experienced Users

This section presents the findings of the interview study of the experienced users. It is divided into several main subsections that tell the story of the experienced user’s perception of the experience with a self-tracking device. The subsections are: the expectations, the adoption of the device and the relationship to personal data, which culminates in the four coping tactics.

The introductory section discusses the user’s expectations of the capabilities of the self-tracking device. It places emphasis on what the user anticipates from engaging in and adopting a self-tracking device, resulting in categories such as the ability to track the self, improve lifestyle, self-assessment, and creating a personal archive. After the expectations, the focus is placed on the experience with the device. This reveals the user’s thoughts on the hardware and software, but also

discusses the data dashboard, the use of notifications and finally describes the new habits that the user embraces. Subsequently, the next section elaborates the user's relationship to data. It sets attention on how the user describes the meaning of personal data and proceeds to introduce the topic of trust of data.

The subsequent section elaborates on what occurs as soon as the user has been exposed to the personal data. The user then starts reviewing, reacting, reflecting and finally responding to the data. This is an exploration of what the user goes through as soon as he or she is exposed to the data. First, the user reviews the data. Secondly, the user is likely to have an immediate and brief reaction. Thirdly, the user might reflect by considering and evaluating the data that has been reviewed and quickly reacted to. Finally, the user may proceed to exercise acknowledgement or activity of the personal data that has been processed in the previous stages. If the user finds the data unsatisfactory, he or she might reject it, followed by adopting coping tactics.

6.6 The Expectations

Prior and post the initial use of the self-tracking device, users have expectations of how it will contribute to their personal experience. The aim of asking the users about the expectations is therefore to gain an understanding of the assumptions of the device and what it would give in return for using it. However, the users rarely articulated a concrete goal while retelling their respective experiences. Instead, the users had expectations of the device's capabilities. Accordingly in this context, the expectations are assumptions of the self-tracking device's capabilities, rather than the expectations of the data and goal-setting. It is not about the end-goal of the user, but rather about the functionalities and possibilities that the device can provide for the user. Even so, it is still problematic to evaluate whether the expectations were the true expectations in the beginning, if expectations changed over time and if they were fulfilled. The difficulties in discussing this also exist because the users often had poorly articulated goals from the outset, which in turn created an uneven loop of activities.

The main expectations are that the device will be able to track data, improve lifestyle, provide self-assessment and create a personal archive for long-term purposes. The users would either have one or several of the expectations.

6.6.1 Expectations of a self-tracking device

The main expectations are that the device will track personal data, improve life, provide self-assessment and create a permanent and standalone personal archive. The users have one or several expectations.

The clearest sentiment in the interview data shows the device was expected to track personal data, such as the user's sleep and step activity. A user stated clearly that *"When I bought the UP a year ago, [I thought] 'how amazing it would be track absolutely everything'"* (JB19, F29, account manager). Another user elaborated: *"What overshadows getting fitter, to be perfectly honest with you, is the geekiness of self-tracking and painting a full picture of myself whether I like it or not"* (FB5, 35, researcher). The interest of tracking is also a combination of the new technology that gives the promise of being able to track personal data: *"I was interested in electronical help devices and apps that would help me track things. I am curious about tracking things that I don't know about. Activity tracking and sleep tracking is something that electronic help is quite helpful. That's why I was interested"* (JB8, M30, entrepreneur).

Despite that fact that different categories of expectations are repeated consistently, the specific reason behind these expectations still varies from being *"for fun"* (JB25, M23, student; JB9, M27, designer) to being interested in the QS community. Those users would mention the community and affiliation: *"I'm all into this Quantified Self movement and it's not the only thing that I use to track myself"* (JB2, M29, account manager). As the user mentions, he would track other aspects that are beyond the capabilities of the device. The QS enthusiasts, however, were not a dominating group.

Beyond tracking data, the expectations are that the device will aid in improving aspects of life. Many expected the device to give motivation to improve lifestyle habits, such as walking or sleeping more. For example, *"I hope to continue for a long time. I hope to just continue. Because it's what keeps me motivated [...] I couldn't have done it without the Fitbit. It's the thing that puts numbers and pictures on it all that makes it all... that makes me continue. I still have big expectations"* (FB2, F40, housewife). Another interviewee claimed that it was *"To motivate myself to exercise more and sleep better. To remind myself of the importance of physical activity and good sleep"* (JB12, F26, digital manager).

Few were explicit about the aim to lose weight, but on rare occasions, a user would confess: *“I’m very interested in losing the baby weight and doing what I can to get back into my pre-pregnancy weight”* (JB17, F35, housewife).

A frequent expectation is that the adoption of the device will inspire and deliver self-assessment in simple ways. For example, a user wanted it to *“empower me to understand more about my behavior over a period of time”* (JB11, F28, engineer). Most users did not mention the QS community and related practices as a part of this self-assessment, yet they did reference that the role of numbers was expected to give a clearer view on themselves. One user summarized the overall expectation of numbers for self-assessment: *“Without those numbers, I wouldn’t really be able to assess myself as well. I think it’s all in the numbers”* (JB17, F35, housewife). Another particularly active user said that *“thanks to the Jawbone, I get a more precise number of what I’ve used calorie wise so I can compensate that with my diet. Instead of just doing a mass estimate and then eating a mass estimate I can get a more precise value on my calorie intake, if I want to be on a negative or positive side”* (JB16, M27, military).

The self-tracking activities were also expected to create a personal archive that would hold value for the user in the long term. A user described it as *“an archive on my activity and sleep”* (JB11, F28, engineer) and *“kind of like a pattern and in the end you get data and you look back and see how you can do better next. Jawbone gives you that”* (JB7, M29, account manager). The act of tracking was seen as a long-term investment that would provide insights at a later point in time. *“It is more to look back how I have done it last period and whether I should change anything. And not so much today in the present, with what shall I do tomorrow. It is more long term”* (JB25 M23, student). These expectations did not necessarily aspire to find quick fixes and make drastic changes but to invest in data collection. Another user said that it would be helpful when encountering health issues in the future and that *“it’s like going to the doctor. It’s just to get confirmed that I am healthy. Also to see deviations, to see if I am out of balance in the data. I’m not looking analyzing every last bit of it”* (FB8, M41, IT manager).

6.7 Adoption of the device

This section presents the user's reflections of the device as an artifact that has been adopted and the experiences that come along with it.

The start of the activity of self-tracking begins with adopting a set of tools, namely the appropriate hardware and the software. The hardware is a device the user wears on the body. The device has sensors that are able to measure the activity of the user based on different parameters. The software is a mandatory complement that allows the user to view the data collected through the hardware. The product of self-tracking is then visualized through the software, which is referred to as the data dashboard. The data dashboard can either be seen on a mobile or computer screen, but most commonly the user interacts with the mobile interface. These are the main tools that are adopted and the user's perceptions of these are presented in this section.

6.7.1 Design of the hardware and software

The design and functionality of the device was debated by the users from both a positive and negative perspective. The topic of the wristband design is the category with most divided camps. By contrast, the functionality of the hardware and software proved more streamlined opinions.

The design of the wristbands fueled divided opinions. The positive camp expressed that the wristband was appealing for various reasons, such as being fashionable, generally attractive or simply transferring positive attributes to the user. One user said *"I think it's quite stylish as well. It has a style factor"* (JB8, M30, entrepreneur). Another user agreed that it was fashionable and that it also gave indication of being a part of a community: *"As soon as you start wearing it, people start noticing it. It's more like jewelry and accessory that is very trendy. If you see people around you wearing it, it means that they kind of care about the same things as you do. It's like a community or something. It's trendy, I would say that it is even a bit fashionable, right?"* (JB6, F29, designer).

On the other hand, another user underlined the neutrality of the design and that *"it's not that it's a fashion statement [...] it's not like you can see this one is a fitness bracelet. It could be a normal bracelet as well because it looks nice and*

casual” (JB24, M23, student). Another user said that *“design wise, I think it is at the moment by far the best kind of casual designed bracelet out there. All the others, Fuelband, Fitbit, they’re just plastic chunks on your wrist that stand out, being too sporty, whereas the Jawbone UP is really neutral. I can wear it with a suit, with a t-shirt or anytime”* (JB2, M29, account manager). Users also thought it was a positive outcome that *“it’s a bit difficult to recognize that Jawbone is a technology on your arm”* (JB24, M23, student).

The design was less appealing to some users, but mainly for practical reasons. Primarily, the design of the bracelet restrained the user from daily patterns, as one user describes: *“I always had to take it off whenever working at the computer - it was in the way. It was also in the way when putting on a jacket”* (JB28 F30, pharmacist). Another user concurred that *“it’s a bit too much in the way”* (JB26, M28, lawyer). This also applied to a sleeping setting because *“It’s a bit irritating to sleep with. When you sleep, you just want to be ‘free’”* (JB31, M29, researcher).

However, the majority of criticism of the device was regarding the hardware, such as malfunctioning or missing functionalities. Primarily, the devices were criticized for breaking: *“it stopped working after a while”* (JB7, M29, account manager) and that *“They break all the time! I hate it”* (JB1, F30, business analyst). The technology was not sufficiently developed to give the user the seamlessness that they wanted, i.e., wireless syncing. Users said that the *“pain with the jawbone is that you actually have to use the headphone jack to sync everything”* (JB7, M29 account manager) and that *“It is a bit annoying that it doesn’t have a bluetooth function”* (JB29, F28, pharmacist).

The activity and step function are also criticized for its lack of tracking beyond a specific set of activities. Many users highlighted the problem of being unable to identify activities beyond walking, such as biking, skiing and weight lifting: *“it’s kind of annoying that you have a goal and you can’t reach it through high intensity workouts, just because you aren’t GPS-moving”* (FB7, M28, lawyer). In this case, this user was weightlifting on a regular basis but the self-tracking device was unable to automatically track the intensity of this activity. This caused a discrepancy in the data as well as individual distress because *“I tend to miss my activity goal daily because of it”* (JB15, M32, account manager).

Another issue was that the device “*application is not working and syncing*”(JB14, F30, marketing manager) but this was primarily related to the Jawbone UP device. The malfunction was due to the device inadequately registering the activity, whether it was sleep or steps. A user shared that “*the device stalled and kind of become unusable so I had to reset it and lost all my data. That was annoying. Also, I’ve had issues with activating the sleep function... it takes a while before it enters sleep mode*” (FB1, F26, nutritionist). In particular, the activation of the sleep mode did not always work or reverted to day-mode in the middle of the night “*which was freaking annoying so I couldn’t see how much I had slept*” (JB21, F36, graphic designer). Not only did the sleep function not always activate, but it missed registering hours during the night when the user awakened: “*I don’t think it recognizes the moments that I am awake even for 5-10min to nurse my baby and put her back down*” which meant that “*I think that I’ve been a little turned off by the sleep bar because I know that it’s really not that accurate*”(JB17, F35, housewife).

Faulty functionalities led to frustration because it mean that the data was lost and it “*will just destroy your stats completely*” (JB25, M23, student). When the device did not manage to continuously update the user’s data archive, due to malfunctions and hardware issues, the user became de-motivated. As a response, the user came to consider the device to be unreliable and inconsistent, which was subsequently reflected in the user’s behavior towards the device. In other words, if the device misbehaved, so did the user. Eventually, it could lead to termination: “*I’ve stopped now because it’s not working*” (JB3, M29, account manager). However, this was not always the case.

The individuality of the app was considered a constraint by some users who wanted to pair it with more apps in order to aggregate various data streams. One user concerned with her nutrition and running said that “*it would be nice that I wouldn’t have to use Endomondo and Myfitnesspal*” and that the perfect self-tracking device would have the “*same functions as these other apps*” (FB2, F40, housewife). Another user said that “*I wanted something that was a bit more complete and tracked everything*” while referencing the need to be able to integrate more apps to her primary self-tracking app (JB19, F29, account manager). The self-tracking device did not have the wide array of functionalities that the user requested.

6.7.2 Data dashboard

The self-tracking device comes with a mobile and desktop dashboard where the user can check his or her data. The user developed a pattern around checking the data. In the beginning it was frequent, but once the initial period had passed, the checking pattern stabilized, regardless of the device the user had adopted. Whether the user was a new or senior user, the interaction pattern did not differ much once the dashboard had been opened. In general, the user would skim through the personal data and perhaps focus on one category over the others, but mostly with the aim of getting an overview of the short-term goal (daily) versus a long-term goal (weekly, bi-weekly or monthly).

When interacting with the dashboard, next to none of the interviewed users perform a deeper analysis of the self-tracking data, such as downloading spreadsheets for further examination. Instead, the user relies on the dashboard to deliver both data handling and insights. A user explained: *“I want the data to be customized and give me advice without me having to analyze the data. Sure, there is a lot of data but I, and other people, are not good at using it. I want feedback and advice, not just data. There is lots of data but we are not good at using it”* (JB9, M27, designer). However, the lack of effort to pursue a self-instigated analysis translated into that the data came across as unintuitive and uninsightful. This failed expectation of gaining self-insight may cause a decreased interest in the data and the device, which ultimately leads to abandonment.

6.7.3 Notifications

The self-tracking device offers several functionalities such as a sleep alarm and an idle alert, as well as various customized mobile push notifications and in-app notifications. These functions are collectively referred to as notifications, since they remind the users of the goals installed by adopting the device.

The sleep alarm is the most popular functionality, which means that the user can set a preferred time interval for when he or she would like to be woken up. For example, the user would indicate that he or she would like to wake up between 07.00-07.30 and the wristband would then vibrate when the user was in light sleep

mode. A user said: *“I wake up from the alarm and I really like it! An excellent way of waking up! That is the feature I think I would miss most.”* (JB29, F28, pharmacist). It was a positive feature for couples *“The alarm clock was awesome, I could wake up without [my girlfriend] having to wake up. That was awesome”* (JB7, M29, account manager).

However, the sleep alarm does not always manage to wake up the users: *“I have difficulty to wake up [...] but most of the time I kept on sleeping and turned it off. So I did set the alarm but it wasn’t that often that it woke me up”* (JB10, M29, account manager). In this case, the user would abandon the function for other options such as a mobile wake up alarm or a standard clock.

The Jawbone UP’s idle alert is also a well-liked and well-used feature. The idle alert functionality allows the device to notify the user when he or she has not moved for a certain programmed period of time, such as 30 minutes or one hour. The period of time is set by the user. Many agreed that besides the sleep alarm, *“the best thing was probably the vibration [alarm] that would buzz if I had been sitting down for an hour at the office, then I would get up and take a few steps, just to get up”* (JB30, M27, lawyer).

However, at times the notifications are considered a disturbance *“I used the idle alert a couple of times in the beginning, but I didn’t like the buzzing, as I’m not a big fan of notifications in general, so I stopped. I get so many emails as it is so I don’t want any other disturbances”* (JB26, M28, lawyer).

In summary, the device has several shortcomings such as clunky design, crashing functionalities and data uploading issues. In the event of losing data, the user was frustrated because it interfered with creating a holistic archive. Although, there were several benefits as well. For example, the adoption of the self-tracking device meant that the user incorporates new patterns of practice, or routines, in the daily life, which are presented further below. The device is worn around the clock and after a while, it is no longer noticed and becomes an integral part of the user. In the morning, the sleep function is turned off followed by a check up on the data to give an overview of the night. The next time the data is checked is usually later in the afternoon or evening to evaluate the day’s progression. However, in the first phase of adoption, the user would continuously monitor the goals, but after a few

weeks, the user checked the data less. The more routinized user would perhaps check in the late afternoon, but more likely would do so in the evening to evaluate the activity of the day.

6.8 New technology, new daily patterns

Along with adopting a new technology, such as self-tracking devices, new patterns are created. The interaction pattern is intense in the beginning but trickles down over time. The patterns that were described by the users in the interviews are presented in this section.

The self-tracking device is worn around the clock, with the only exception being the time used to take a shower: *“I wear it 24/7 and I only take it off when I’m in the bath”* (JB22, F47, administrator). The device is worn constantly and eventually, it becomes an unnoticeable and integral part of the user who embraces it: *“it’s just a part of me. I got used to that. If it breaks I will just buy another one. Just as a toothbrush. It’s just a part of my daily life”* (JB1, F30, business analyst). Another user agrees *“I’ve been using it for a long time, and now it has just become a part of me”* (JB31, M30, researcher).

Initially, the user developed the habit of regularly checking the personal data throughout the day, with a minimum of two times, yet sometimes up to five times. Some users checked the data even more often than that in the first months of the adoption: *“In the beginning I would check it like four to five times a day. But the focus would be morning and evening”* (JB3, M29, account manager). Another user explained: *“I look at it three to four times during the day, just to see how things stand, because there is some satisfaction in achieving ones goals or to see how much you have moved [...] it is mainly in the morning and evening I look at the app”* (JB25, M23, student). Generally, the user would check *“A lot in the beginning but then it just dissolved and became less and less. Once a day in the beginning then less and less”* (JB7, M29, account manager). This indicates that the early adoption pattern was emphasized with regularly checking and monitoring the data.

As time passed, users would check less regularly and primarily do so in the morning and in the evening. When asked how often the data was checked, the

users said *“I’d say every two days. I sync it not every day but about every two days, then I check. I look at how long I slept [and] the averages”* (JB8, M29, entrepreneur). The pattern of decreasing checking of the data was common: *“At first it would be every day, a couple of times a day, but then it would be around once every third day or so”* (JB9, M27, designer). The checking of activity data is monitored in the beginning of adopting the device but is eventually so routine it is checked less often.

When looking more closely at the patterns, it can be clearly seen that the user commonly checks the sleep data in the morning: *“I would wake up and then I would synchronize just to see how I slept. To see if it had been a restless night or if it was a night where I had good sleep”* (JB10, M29, account manager). Another user also shared that the first thing he does is to *“register the nights sleep”* and then *“see how much I slept, then I put it back on”* (JB16, M27, military). It is also used to reflect on previous sleep results: *“I really like the sleep data so I use to check that when I woke up or when in the bus to work and kind of compare to previous days”* (JB7, M29, account manager).

In the afternoon, the main purpose of checking is to see how the data has accumulated over the course of a day. A user explained *“I always check the app in the afternoon for a status update. It is at that time I upload my data and see whether or not I have reached my goal for the day”* (JB22, F47, administrator). If the user does not check in the afternoon, he or she would do so in the evening: *“I would sync it in the afternoon to see how far I had gone. Then I would sync it at night then activate sleep mode”* (JB21, F36, graphic designer).

The data is also checked after the user has performed some type of activity: *“When I wore the bracelet every day, I normally used the app about 2 times a day: in the morning when I woke up and in the evening when I went to bed. Sometimes I also used it after work-out if I wanted to save the train details in the app immediately after the workout.”*(JB12, F26, digital manager). Another user concurs when he says *“I check when I do sports; then I wanna see my data”* (FB7, M28, lawyer).

6.9 The individual perspective on personal data

This section presents the user's perspective on data by revealing the user's understanding about the meaning of data as well as the degree of trust that the user holds for the data.

6.9.1 The meaning of data

It is important to distinguish how the user views and makes sense of the data that is provided by the self-tracking device.

The data is seen as some type of personification or a *“mirror of the self”* (JB2, M29, account manager). A user felt that the personal data is *“my personal achievement. It's something that has been going on. Then it's processed in a very nice way in this dashboard and sort of constant feedback of what's going on. Data for me is just what has been transformed into something”* (FB4, F28, researcher). Another user elaborated that *“It gives me facts as to what I think I do and I actually do”* followed by that it *“gives me a picture of how my health and living right now”* (FB7, M28, lawyer). The data is therefore an embodiment of the user's performance or lived experiences by aid of the technology.

Even though the data is considered as a personified embodiment through technology, it should still be viewed with hesitation because *“it is always something that is half of the truth, I think. I think having data and making decisions on data is important, but you should always consider the human aspect in there as well”* (JB4, M30, entrepreneur). The users meant that the data might be an embodiment of the self, without being an absolute truth because some aspects might be omitted, and should therefore be scrutinized. The data only exists because it is in relation to something, like the goals. A user said that the data *“only rates well if you compare to something that doesn't rate well”* (FB7, M27, lawyer), while underlining the importance of considering in what context the data is compared.

On a general level, the concept of data does not have a particularly prominent role in everyday life: *“I'm a bit in between. It is important in some ways but also not at all”* (JB26, M28, lawyer). Another said that *“It doesn't mean that much to me. It's*

just like a fun gadget to wear and I think it's fun to look at [the data]" (JB23, M23, student).

On the other hand, some saw data as *"facts and proofs of what I've done"* (JB32, 61, administrator). It is *"like going to the doctor... it's just to get confirmed that I am healthy. Also to see deviations"* (FB8, M41, IT manager). The data as facts gives the possibility to explore performance with different parameters and eventually identify issues. Furthermore, another particular keen self-tracking user said that data *"is a means of gaining insight into an action that influence things that we care about, in particular my mood. I don't really enjoy doing self tracking at all - I kind of just do it out of necessity. So I see it as a necessary element if you are trying to identify a solution to a problem yet unsolved"* (JB20, M30, entrepreneur). Another keen user elaborated that data *"holds me accountable to eating well, staying fit and being active. Without those numbers, I wouldn't really be able to assess myself as well"* (JB17, F35, housewife).

Through the increased knowledge that the data offered, the data was also seen as a way to gain or reclaim control of personal behavior. One user simply said that the data means that *"I can have more control"* (FB7, M27, lawyer) while another elaborated that control is empowerment because *"data should empower me to understand more about my behavior over a period of time"* (JB11, F28, engineer).

6.9.2 Trust in data

During the interview, the concept of trust was not defined to the users who were interviewed. When the users were asked if they trusted the self-tracking data, the answers were at times polarized. A select few were on opposite sides of trusting versus not trusting the data, but most commonly, the user would state that there was a certain degree of trust.

Some users trusted the data a great deal. A user revealed that *"I am actually putting a lot of trust in that it's measuring my activity correctly"* (FB4, F28, researcher). The trusting users had often tested the device to retrieve results that in turn reinforced the element of trust: *"I have personally tested it myself and I find the data trustworthy (...) I fully trust the devices"* (JB22, F47, administrator). Another user shared that *"I've been walking with someone who also has the device*

and we kind of compare the steps, and there is a big similarity, then that's good. So I guess that I trust the similarity [of the data]. If I didn't trust it, I probably wouldn't wear it" (FB4, F28, researcher).

On the other end of the spectrum, skeptical users found that they did not trust the data. This was mostly the result of a specific category of data, such as sleep or step activity, rather than the overall data. A user said *"I don't really put too much faith in it because, for example, I know that over the last few nights I've woken up three, four times [...] but in the data there is usually only one [time]"* (JB15, M32, account manager). This was often based on unfamiliarity with how the technology worked which was exhibited in statements such as: *"I don't really know how they calculate it. I don't trust the calculation"* (JB8, M29, Entrepreneur). The lack of trust often stemmed from the possible limitations of the technology because it was not adequate enough to measure activity perfectly. Yet despite a critical tone, many of the users remained—and remain—avid adopters.

As mentioned, some users didn't fully trust the device due to insufficient understanding of how the technology works: *"I don't know about the technology and how to interpret it. Probably generally, it's somewhat accurate. I just don't know"* (JB13, F31, project manager). Another user with the same considerations elaborated that *"I was wondering about my movement, how it all hangs together, and how can they measure my sleep? So I'd say that I'm a bit suspicious. I don't take it all too seriously, rather as an indicator"* (JB28, F30, pharmacist). The users were unsure of how the technology worked but still remained interested in acquiring and interacting with the data.

Beyond the particularly positive and particularly negative users, many users express contentment with the data; thus, they trusted it sufficiently enough to continue using the device. These users said that *"I trusted [the data] but I took it with a pinch of salt"* (JB3, 29, account manager) or *"On a general level I feel that I can trust the Jawbone statistics"* (JB14, 30, marketing manager). Moreover, a user said that *"I trust the numbers for what they're for, like to give me indication"* (JB3, M30, account manager). In other words, the output of the personal data was trusted to some extent by some users.

While carefully trusting the data, the users also consider aspects such as accuracy of data, technology and trends. The most common critique that caused some users to not fully trust the device was the accuracy of the data—or lack thereof. Some bluntly uttered *“I know for sure that it is not 100% accurate”* (JB6, M29, designer) while others said that *“there are some inaccuracies so in some ways it’s made me a little hesitant, but generally speaking it’s pretty accurate”* (JB13, F31, project manager). However, the user would still use the device despite viewing the data as inaccurate at times. These users agreed that *“it’s a tool, just a tool, to move more. It doesn’t have to be precise or exact 10 000 steps, just as long as I get up there”* (FB10, F24, sales assistant).

Many times, the inaccuracy of personal data was overlooked because the self-tracking device was considered to deliver a consistent pattern or trend. Users mentioned that the data was being used *“as a rule of thumb”* (JB11, F28, engineer) and it was *“not 100% but it is a guide of where you are at”* (FB3, F26, store clerk) because *“at least it is some kind of benchmark”* (FB9, M42, teacher). In essence, it was seen as *“a tool to be more mindful but not actually the main vehicle to achieve it”* (JB2, 30, account manager).

6.9.3 Failed expectations of data

The expectations were not always met by the interviewed users who, in turn, expressed frustration over how little had changed due to wearing the device. For example, the *“Jawbone will give you indication of how lazy or not lazy you are but then if you are changing your lifestyle it can’t give you much more.”* (JB7, M29, account manager). A user said that *“it doesn’t really [give] insight that pushes amazing messages. If you don’t use it you can still measure your week without this device”* (JB5, M29, account manager). Another user also stated that the *“benefits of the wristband is not worth the effort. I want it to be more seamless”* followed by the fact that *“it didn’t change any behavior. I had expectations about the data but it was just there, without recommendations and personalization”* (JB9, M27, designer). The expectations failed to change behavior, which resulted in disappointment, ultimately leading to a decline or complete lack of use of the self-tracking device.

When the expectations were not fulfilled, regardless of the initial expectations, the blame was often directed at immature technology. For example, a user expected *“that it would provide me with a more fair picture of my sleeping habits, but since it doesn’t measure pulse, its technology were not able to do that”* (JB32, F61, administrator). Instead of reflecting on personal engagement in the behavior change process, functionalities such as wireless access, heart rate measurements, integration with other platforms and automatic activity identification were requested by the users.

6.10 Exploring the process after exposure

This section presents four occurrences that happen after the user was exposed to data, namely reviewing, reacting, reflecting and responding. These are all steps that occur from the point at which the user is exposed to personal data and onwards to the immediate reaction, subsequent reflection and finally the response.

6.10.1 Reviewing data

Review takes place as soon as the users are exposed to the personal data in the chosen dashboard. The data is usually visualized in graphs to make it easily comprehensible. Thus, the users are not exposed to raw data in a csv-file or Excel file. The review marks that the users are exposed to the personal data and scan through it for a briefer time period.

The reviewing most commonly occurs in the morning and in the evening, as explained earlier in the habits developed by the users. The first check when *“I would wake up and then I would synchronize just to see how I slept. To see if it had been a restless night or if it was a night where I had good sleep”* (JB10, 29, account manager). The second check occurs *“Usually in the evening [to] I check how far I’ve gone during the day”* (FB9, M42, teacher). Another interviewee was a little more precise and added that the review occurs *“usually closer to the evening time because I want to see how many steps are left, like if I am close to my goal or if I am far away so I need to walk a little bit more or exercise or something like that. So around 5 pm - 6pm”* (JB1, F30, business analyst).

The users review the data that is most relevant to them at this point in time. A typical user described her usual interaction with the mobile app: *“I would look at the home page and the two bars. Then I would look at weekly trends, daily trends. I would click in on the bars. Calories burned were never really interesting. I was mostly interested in steps. I would look at number of steps registered. Then I’d probably zoom out and look at weekly trends and across a couple of weeks”* (JB19, F29, account manager). Another user said that he would check *“the graphs that appear on the first page. I would click on them sometimes, but not always”* (JB7, M29, account manager).

The reviewing process was rarely lengthy but mainly consisted of the user opening the dashboard and then performing a scan. The users looked at the main page to get an overview of the overall results. Most users explained that they would usually check the *“numbers in the bar chart. That’s absolutely the most important thing that I follow up on when I open the app”* (JB14, F30, marketing manager). Another said that *“I would open the app, I would go in, I would look at the bars and then I would go in and tag activities that I did during the day. For example, if I would go into the gym I would tag those and put in what I did. That’s basically what I would do”* (JB3, M29, account manager). At times, the users would also input additional information, such as adding precise activities that could not be registered by the device, like weightlifting, swimming or biking.

While reviewing the data, the users exhibited selective behavior, such as mainly paying attention to only some parts of the data: *“I don’t really pay attention as much to the activity, more just if I’ve hit the goal”* (JB13, M30, project manager).

Users appreciated an uncomplicated design that gave a quick overview of the data. *“The Jawbone is quite simple. It put things into graphs so you can see things instantly so you don’t have to sit and load that specific data. That makes it easy to see what’s good and what’s bad regarding you work out”* (JB23, M23, student). However, the simple design also meant that: *“You can’t compare it right away. You just see a stream of data but it’s quite short also. You don’t really see the whole picture”* (JB8, M30, entrepreneur). The simplicity of the design gave limited possibility for the user to analyze the data, and gave just a general impression. In this respect, it was up to the user to pursue an analysis, which often did not happen.

Beyond going over a general overview of the data, the users checked the data of other social connections: *“I would look at the percentages that I have reached out of my goals. And how far I am from my goals from today. That’s the first thing. And then I usually flicker down to see what others have done”* (JB2, M30, account manager). The social component is discussed further in the following sections, since it is a category that invokes reaction, reflection and response.

6.10.2 Reacting to data

The second occurrence is the immediate reaction that occurs after the user has scanned the data. The reaction is immediate and then users move on , which makes it seemingly more emotionally grounded rather than a lengthier, more elaborate and a more rational contemplation.

6.10.2.1 Goals

Both reaching and not reaching a goal will foster some kind of reaction. The users described that they experienced a brief yet positive feeling when they reached a goal. The users felt that it *“was a good feeling when you were reaching a goal”*(JB3, M29, account manager) as well as *“Good and satisfied. It makes me feel I’m a good person. An active person taking care of my health”* (JB12, F26, digital manager). Another user said that completing a goal gave a *“Happy, refreshed, alert, good”* reaction (FB3, F26, store clerk). One user elaborated that *“It’s a little victory when you do well but it’s completely ridiculous, because it’s just your steps. [...] nobody can alter it or fake it: you’ve done those 10 000 steps and that’s a good feeling. So you kind of feel like ‘I’ve done good today’”*(FB4, F28, researcher). However, many times, the user’s main reaction was a mild but content feeling: *“I feel satisfied at least. For me it doesn’t really last - long just for 5min. Not even excitement but just ‘Ok, I did well’”*(JB6, M29, designer).

The feeling of overreaching the goal was a strong and satisfactory reaction: Another mentioned *“I’m happy when I’ve reached my goals, especially when I have far outreached my goals”* (FB6, F30, geologist). One user compared it to merely meeting the goal and said that *“it’s when I go way beyond that I’m happy”* (JB18, F38, researcher). Exceeding the goal was seen as a personal triumph.

When a goal was not reached, it was “*a stronger sensation than reaching your goal*” (FB5, 35, researcher). In this case, the reaction was more intense and slightly more extended, while often causing chain reactions, such as reflection, strategic thinking and the aspiration to alter behavior. It was often described as “*disappointing*” (JB6, M29, designer) and “*it annoys me*” (FB7, M28, lawyer) not to reach a goal. Another said it left her “*A little irritated actually. It makes me feel lazy and I feel self-conscious about it*” (FB3, F26, store clerk). However, a select few said that not reaching a goal did not produce in them a strong reaction “*It doesn't really mean much*” (JB1, F30, business analyst) and that will only “*affect me for two seconds but not long term effects*” (JB4, M30, entrepreneur).

Some users also reacted by feeling that the self-tracking device exerted a sense of control. Many times this was due to a goal that was considered difficult to attain, which led to a user feeling “*very stressed from looking at my data, when it was bad*” (JB28 F30, pharmacist). Another user said that he would only check the app once per day because “*If I'd look at it more often, I'd just get stressed and feel that I have to perform more*” (JB31, M29, researcher). These users experienced the interaction with personal data as a control mechanism that stressed them. The sense of being imposed upon by this control over their actions spurred an emotional reaction, rather than a reasoned reaction. Sometimes, the reaction led to guilt. In order to cope with this reaction, the user generally did little reflection; instead, he or she responded by altering behavior, such as decreasing interaction with the data and its social aspects.

6.10.2.2 Other people's data

The reactions go beyond personal data, and can also include reactions to other users' data. Some users felt that being exposed to the data from social connections brought up intense emotion. If a social connection performed better, especially in the step activity, a negative reaction would be imposed on the user. For example, one user explains that “*when I see that someone has totally surpassed their goal and I feel like 'Oh god, I'm so lazy'*” (JB13, F30, project manager). Another explained that the reaction was to not lose, but to beat the other person and that “*It just made me always want my goals be at least above one hundred percent*” (JB10,

M29, account manager). The reaction to social connections led to greater reflection and sometimes more serious response.

6.10.3 Reflecting on data

The third occurrence is characterized by reflection, which involves the process of assessing the data that the user has just reviewed and then quickly reacted to. Therefore, this is the first time the user starts evaluating the personal data beyond the immediate and swift emotional reaction. However, this may or may not be a lengthy process. Usually, the user puts the personal data into context by considering various aspects, such as whether the results are probable and reasonable, as well as if they satisfactory.

6.10.3.1 Goals

The user sees the data visualization as an opportunity to reflect on the self that will ultimately lead to being more knowledgeable about the self. One user said that *“It made me more knowledgeable about myself”* (JB3, M29, account manager), while another proclaimed that wearing the device is *“a type of consciousness. I’m just conscious of what I am doing”* (JB1, F30, business analyst). The self-awareness was not only spurring on consciousness, but it also *“keeps me accountable”* (JB13, F30, project manager). The user reflects more about the self when engaging in self-tracking because of the exposure to personal data, which in turn leads to an increase in personal awareness. The personal awareness ranged from positive to negative aspects and often inspired the desire to make changes in behavior.

Users reflected about personal performance after reviewing and reacting to personal data, which increased personal awareness: *“If I wasn’t able to track these things I would have absolutely no idea whether I was way doing the right amount or way over, and if I reached the right amount it would be pure luck”* (JB24, M23, student). Another user said that *“You can get some statistics on yourself, so it’s not just the feeling of ‘I’ve done something this day’, but I can actually see that I’ve done something. It’s a little more factual, as you can prove it”* (JB25 M23, student). The user was pleased to be able to have concrete facts rather than having to rest upon intuition to evaluate daily personal performance. Overall, users became more knowledgeable about personal performance.

By gaining such awareness, users were able to reflect on problematic areas of daily patterns of practice. For example, a user was troubled by *“seeing how little I actually move when I am in the office. I mean, I spend a lot of time there and when you can see that you are only getting 2000-3000 steps in a day it’s really a little scary. You should be moving more!”* (FB4, F28, researcher). Another user agreed and said that *“it was interesting to see how little I actually move when I’m at work. I felt a bit bad over that. It was a bit shocking”* (JB29, F28, pharmacist).

When the user does not reach the goal, a common reflection is that *“this is just not good enough’ [then] there is a contemplation about why I haven’t reached the goal”* (FB1, F26, nutritionist). The reflection after the initial unsatisfactory reaction was to feel some distress and then consider the reason why the goal had not been achieved. Further, some users became upset by unsatisfactory data: *“I really start to beat up myself about it. So I’ve definitely gotten down on myself. Especially if it’s two days in a row for some reason. Even if it is one day where I am on a good track and hitting my goal and [then] one day short, [I feel] disappointed, like you weren’t good enough”* (JB13, M30, project manager). However, users were mostly mildly discontented, as noted in the reaction.

The inability to reach a goal may inspire the user to reflect about what to do differently which can lead to aspiration desire to change behavior. Other users supported this: *“if I don’t reach my goals, yeah, I kind of think about it. But then I just think that I’ll do something about it the next day instead to get the steps. I guess it’s important to get a good average”* (FB9, M42, teacher); *“it just gives me a disappointed feeling so the next day I’m determined to meet that goal”* (JB13, 31, project manager). The users stated that they realized the lack of personal data to meet the goal triggered their ambition to change behavior, especially when it came to the step activity.

However, reflection did not necessarily entail a deeper analysis: *“I cannot say that I have explored all of [the functions]. I would say that this thing where you can register how you feel, I haven’t really used that. I can’t say that it’s not really interesting, but I haven’t figured out what I want to get out of it”* (JB18, F38, researcher).

Users identified both negative and positive aspects of the daily routines. One user was particularly pleased by her sleep patterns: *“I had always thought I was a light sleeper, but it turns out I sleep very deep after all”* JB28 30, pharmacist).

6.10.3.2 Other people’s data

The self-tracking device allows the user to add other users, which makes it possible to view others’ personal data. The integration of this social element allows new aspects to be uncovered, such as competition, comparison and the creation of new benchmarks. The users that were interviewed had none or only a few social connections. This was primarily because too few in the users’ network had adopted the same device and a user said that *“I would have more if people would use the Jawbone app”* (JB2, M29, account manager). However, the general outlook was positive towards integrating a social element to the self-tracking endeavor.

When it was available, however, the social network invited the user to observe the results of other users. The interaction with *“this mini community was fun and the most rewarding because it was always something to check. Something needs to happen in order for me to keep interested”* (JB9, M27, designer). All the same, as mentioned in the section on reaction, some users found it initially stressful to view other’s data, since it presented a possibility for comparison, but for others this was not the case: *“It’s really interesting to see other people’s data and kind of see what their day has been like”* (JB12, F26, digital manager). Another user agreed and said that *“you want to see how much other people work out, how much they sleep. I like the graphs. I think it’s cool to compare my sleep patterns against someone who I know is roughly a similar character or in same phase in life”* (JB2, M29, account manager). A third user did not actively pursue a comparison, but reasoned it was embedded in the interaction: *“I don’t necessarily compare myself to their data. But I think it’s kind of natural behavior to think about it for a second”* (JB13, F30, project manager).

Some users started thinking in competitive terms when exposed to data that was related to their goals and related personal achievements. The element of competition surfaced in both individual and group settings.

Individually, the user stated that the primary competition was against the self: *“I feel that internal competition. It's like when I run. I need to improve my results every time.”* (JB22, F47, administrator). Individual competition could be discouraging because *“with Jawbone you are competing with yourself which is the worst because if you go down you get angry with yourself”*(JB24, M23, student). However, when the personal data was particularly high in relation to the goal then *“It was especially cool to see when you overpassed your previous goals: ‘today I played badminton this hard’. Good feeling. That’s cool. Because you are kind of fighting against yourself”* (JB7, M29, account manager). The goals caused the user to compete against him or herself. The competition was sometimes about improvement, but often came across as a more playful element that simply spurred the user to continue the self-tracking activity.

The user also reflected about competition when he or she had one or more friends attached to the social network provided by the device and mobile app. The element of competition fuels motivation and provides an additional incentive to improve performance. A user suggested *“the more people that know about it, the more competitive you get and the more maybe sensitive you are to changing behavior, and see the opportunity to change the behavior”* (FB5, M35, researcher). Taking part in outside data was a clear motivation to increase personal results: *“It just made me always want my goals be at least above one hundred percent. I suppose that it is about beating my friends as well as to show who is doing the best job”* (JB10, M29, account manager). Another simply said that *“There is nothing better than beat your friends”* (JB24, M23, student).

6.10.4 Responding to data

The fourth occurrence is response and takes place when the user has reflected on the personal data and then proceeds to act or not act on the reflections made. The response may be to be actionable, such as taking an extra walk to get more steps.

The response is generated by the user based on reviewing, reacting and reflecting on the data. The response is not pushed by the system or device itself.

6.10.4.1 Goals

When the user has consistently reached the goal, the response is to aspire to continue reaching the goal. This was especially apparent in situations where the user had successfully reached the goal over a period of time.

At times, also, when the user response would be an attempt to go beyond the preset goal: *“I know that with myself that if I walked 4500 steps one day, I knew I wouldn't allow myself to walk any shorter distance the next day. So for me it was a great way of keeping motivation up and to keep pushing myself”* (JB10, M29, account manager). Further, the desire to meet a goal was more likely to translate into action if the user executed it immediately. One user said *“When you were not reaching a goal sometimes you were ok with it, sometimes you were like ‘No, I’m going to go for a walk now’”* (JB3, 29, account manager). Another user said that: *“I went out for walks. I did that every time I hadn’t reached my goal”* (JB31, M29, researcher). The users who altered behavior immediately were more successful than those who postponed it until the next day.

On the other hand, some users argued that the data and related goals had little to no impact: *“I don’t really care that much about the daily goals”* (JB23, 23, student). Another said that the goals *“didn't really help me exercise more or become fitter, to be honest, so I didn't see the need in wearing [the device] anymore”* (JB19, F29, account manager). Another user argued that the data eventually became redundant because it *“didn't change any behavior. I had expectations about the data but it was just there”* (JB9, M27, designer). However, the same set of users who claimed that the goals and the data related to the goals did not impact them or their behavior, simultaneously expressed that it was *“fun”* and *“felt good”*, particularly when reaching a goal and seeing positive progress in results. Furthermore, the same users responded to not reaching a goal by gaining self-awareness that triggered a desire to improve. As a result, the claims of non-reactions and a critical tone are distorted by self-perception, as the users indeed admitted to some extent.

Due to exposure to the personal data, regardless of whether it was satisfactory or unfulfilled, some users responded by making plans. For example, one user described a regular evening: *“before I went to bed I checked the data, it’d say how many steps I needed to reach my goal - and then I’d go out for a walk. I felt that I*

needed to finish it every day, so I went out for walks. I did that every time I hadn't reached my goal" (JB31, M30, researcher). For another user, it was more about small choices, rather than taking action. The user said that it *"influences if I eat more cake or not. It's not a very big influence but it makes me think, consider, what has been going on"* (FB6, F30, geologist). To such users, planning created a way to be engaged in behavioral change: *"My lifestyle pattern has changed. I'd never ever go all these extra walks if it wasn't for my Jawbone goals"* (JB31, M30, researcher).

Nevertheless, the response after reviewing, reacting and reflecting on the personal data was rarely to change the goals placed by the self-tracking device. These goals were usually kept as a default and seldom changed. A user said: *"I had 10 000 steps and always the eight hour sleep. I did consider changing it but then it said 10 000 steps was recommended from some American federation"* (JB3, M29, account manager). Another user also kept the same goals: *"I stuck with 10 000 and 8 hours a night. Even if I don't ever make 8 hours of sleep I haven't changed them because I still think they are ideal numbers, even if I can't make them"* (JB11, F28, engineer). The users chose the suggested goals based on the initial recommendation and most commonly kept the adopted numbers as a default or a benchmark for their activity.

In the event of changing the self-tracking goals, the change will primarily be upwards, rather than downwards. The user will adjust upwards when the recommended goal proves to be easily achievable and the user wants a challenge. One user explained: *"in the very beginning when I started to use it, I think I went with the recommended values but after a while I realized that I am moving than what they recommended so I upped the amount of steps, activity, taken"* (JB2, M29, account manager). He then described that he made the change *"To push myself beyond my limits"*(ibid). Other users also reasoned that they change the goal upwards because *"Because it was too easy on recommended"* (JB24, M23, student). It also worked as a motivator *"My goal was at first 10 000 steps and I would make an effort to reach that. I quickly found out that I got a little lazy once I had reached my goal so I put it up to 12000 steps... and once I had reached that a bunch of times then I set it up to 15000 steps per day"* (FB3, 26, store clerk).

On rare occasions, the goal would be adjusted downward, yet this was done with hesitation because, as one user put it: *"I would feel like a wimp"* (FB5, M35, researcher). Some users adjusted downward to allow themselves to keep feeling motivated to commit to self-tracking. A user described his dilemma: *"I'm working in the office mostly at a desk, so if I am not walking around a lot, I know that I can't make 8000 steps or 10 000. So of course, this is a bit frustrating, every day, to not reach your goal. So to be motivated I'm going to decrease the goal a bit"* (JB4, M30, entrepreneur). Another user clarified her reasoning for starting with the recommended goals but then adjusting downwards: *"I started with 10,000 as my personal goal, but I soon realized that I would never reach that on a normal day, so I put it to 7,500 instead. I don't always reach it"* (JB29, F28, pharmacist).

Typically, however, the user would not adjust the goal downward even when he or she was not regularly meeting the goal or was never meeting the goal. It was more likely that the user would abandon the self-tracking device altogether. At times, this logic also applied to users who would consistently meet the default goal. In such cases, the user would not change the default goal but abandon the device: *"It just told me that I was exercising various levels depending on my work schedule. It didn't really help me exercise more or become fitter, to be honest, so I didn't see the need in wearing it anymore"* (JB19, F29, account manager).

6.10.4.2 Other people's data

The social element incorporated in the self-tracking gave the user the opportunity to respond to others' data.

The increase of data sources, such as the data belonging to others, sometimes caused the user to respond by excluding other users due to distress. One user explained that she had initially included other users but after awhile this became a source of unwanted control. The user elaborates that she responded by the following: *"I have chosen to exclude friends' steps in my dashboard because I felt that I got a stomach ache every time I went in to check my stats. I mean, I would compare myself then. I wanted it just to be about me, and my activity and not about others' activity"* (FB1, F26, nutritionist). As a result, the response was to exclude others so that it was not possible for the user to see their data.

However, some users responded to others' data positively and thought that the personal data was enriched by the comparison, and therefore responded by adding new connections to the social network with the specific aim of increasing the individual motivation that came from competition: *"I just recently started to connect to other Fitbit friends and that was because I needed a little bit more motivation to keep going. So I added some which are above my level"* (FB8, M41, IT manager). In this case, the social network works as a positive control and therefore as a motivator for the user to continue reaching the goal. The response to reflection about their own data was to place it in relation to the data of other users.

The gain of a larger network for comparison of personal self-tracking data caused some users to respond by altering behavior with the intention of achieving a stronger step or sleep result. For example, in a Berlin-based office, all workers wore the Jawbone UP for a period of time. One of these users shared the information that the response to being connected to other self-tracking individuals in turn encouraged the same behavior: *"everyone wanted to have the most steps and wanted the most hours of deep sleep. Yeah, very kind of friendly competition, but at some point I know that someone took more steps yesterday just to be on top of the list"* (JB4, M30, entrepreneur). Another user agreed that she *"would like walk an extra route just to get before the other person"* in her friendship group due to mutual competition (FB3, F26, store clerk).

The social element included responses such as friendly interaction, that is, a way to give and receive feedback from others: *"the sharing function is quite strong so when I do record something, I do have a lot team members that are commenting on things"* (JB8, M30, entrepreneur). Beyond the enjoyment of receiving feedback, the user also enjoyed giving feedback to others: *"I like to give my husband encouragement on days that he does not have a lot of activity and on days he is very, very active. [...] I constantly check in with him because we support one another"* (JB17, F35, housewife).

Nevertheless, most users were hesitant to share personal data online beyond the Jawbone UP and Fitbit dashboards, e.g., social media platforms like Facebook and Twitter. One user said that *"I don't really share my achievements on other social platforms. I don't want to spam people with my fitness and achievements like that. I don't really want those in the public domain"* (JB19, F29, account manager).

Another user emphasized that it was too private to share: *“It is quite personal. So the people that use Jawbone, it might be worth for them to see what other Jawbone users are doing, but I don't feel that everybody that I am connected to vaguely should see how many hours I slept or when I went to bed or my workout in the morning. You know. I think it's a privacy matter”* (JB2, M29, account manager). Another user agreed frankly *“I don't share data on other platforms. Period. I don't like sharing data. People don't need to see what I am doing. I don't want them to”* (JB16, M27, military). Instead, the users *“enjoy the intimate build”* of the Jawbone UP community (JB13, F30, account manager).

While the user is not keen on sharing self-tracking data on online platforms, he or she might respond by discussing it offline. It is considered a *“a brilliant conversation starter. People will see it on your wrist and they will go like ‘oh is that one of those’ [...] it's engaging people to talk about their health and in a way connect you with new people you haven't met before.”* (JB2, 29, account manager). Users would share details about the personal data and progress not only to family and close friends, but also to new acquaintances.

Offline discussion was also about sharing small personal successes. The positive results, such as reaching a daily goal, could cause the user to immediately share: *“Sometimes I'll tell people that I hit my goal”* (JB13, 31, project manager). Another user said that when he has reached his goal he has a hard time *“not [to] say anything if I'm close to someone else”* (FB5, 35, researcher).

6.11 Rejection: The four coping tactics

A possible, and often recurring, response after reacting and reflecting on the personal data was to respond by rejecting the data to various degrees, which in turn generated coping tactics. This was particularly common when the user found the results unsatisfactory to deal with and therefore attempted to attach reason to them.

As soon as the user was exposed to data that showed unsatisfactory data, a string of justifications were brought forward to consider why the goal had not been met. The value of the goal was no longer explicit but rather placed on a grey scale where the user seemed to internally debate the validity and importance of the goal.

The user would simply reflect on why the goal had not been reached and often try to find a way of coping with it.

The interview data suggests that users did not always accept the information as it was (i.e., goal attained or not attained), but instead reflect on it and come to new conclusions and justifications. The response to these reflections is referred to as coping tactics in this research. Four coping tactics when not reaching a goal were identified: dismissal, procrastination, selective attention and intentional neglect. The coping tactics aided the user in not having to deal with negative emotions related to the exposure of unsatisfactory data.

The different forms of rejection are elaborated in the four coping tactics below.

6.11.1 Dismissal

The most common coping tactic is dismissal, where the user simply does not acknowledge the information provided by the software. This may include details in the data but also the data as a whole. This predominantly occurs when the information is unsatisfactory, such as an incomplete goal. The user thus chooses not to attribute the results to the self and passes them over.

The dismissal is fuelled by the user arguing that the he or she could not achieve the goal due to the current circumstances. For example, the user stated that he *“did not have the possibility to change it, because you do not have more time in the course of a day, just because you now know that you are not moving enough”* (JB25, M23, student). Another stated simply that *“I have days that I don’t reach my goals, because I can’t”* (FB8, M45, IT manager) and that *“I couldn’t have changed that anymore because of my lifestyle”* (JB19, F28, account manager). In these examples, the users are not able to reach the satisfactory results due to constraints in everyday life. Other users who did not reach the preset goal stated that it was not possible to do so, often by referring more specifically to the lack of time. One user said that *“I can’t change the past anymore so I just see it as a way to get an overview of my behavior and maybe change them in the future but not thinking about the past”* (JB4, M30, entrepreneur). In many ways, the inability to complete the goal is regarded to be contextual. *“I know I can’t reach the goal because I was in the office in a meeting all day ”* (JB4, M30, entrepreneur).

However, these users would rarely change the preset goal downwards, despite regularly not meeting the goal.

Dismissal might also be influenced by how far the user was from the goal. One user explained: *“The days I don’t reach my goals it all depends on how far off my target I am. If it’s only a few steps then I don’t mind”*, followed by elaborating with a typical and recurring comment related to dismissal: *“If I know the reason I haven’t reached the goals, then I don’t mind”* (FB1, F26, nutritionist). Another user said that the data was dismissed but that it didn’t matter too much. However, in these circumstances, the users still mentioned some type of circumstantial reason as to why it did not matter. One user said that *“sometimes it was ok because I was hungover probably or like something like that”* (JB3, M29, account manager). Another said, *“It doesn’t have very strong effect because I usually know why I haven’t reached my goals. Often it has to do with, because I didn’t wear it, especially the step goal”* (JB8, M29, entrepreneur). In both of these latter examples, the users express reasons to the unsatisfactory, which suggests that the users felt compelled to explain their shortcomings.

The above rhetoric was sometimes followed by blaming the device functions by stating *“I could perform much better if the dietary functioning was better”* (JB25, M23, student). The user thus rejects certain results because they are not satisfactory by claiming that improvement could be made if a certain functionality in the device was better. In another but similar occurrence, the user clearly distrusted certain functions and proceeded to dismiss the results. However, the distrust stemmed from gaining unsatisfactory results based on the negative experience of receiving the information. Another user said that the it *“really annoys me that the device cant understand that you are lifting weights [...] I’ve had sessions where I’m almost throwing up and it only shows you had a little bit of activity. Then I would just look away from it”* (FB7, M28, lawyer). In this case, the user described the fact that despite the efforts to influence the goal through being more active, the results remained unsatisfactory. This then led to dismissal of the information provided by the software.

Dismissal could also be triggered and heightened by social relationships. If a user saw unsatisfactory results and then saw others who had performed better, this could lead them to adopt dismissal. For example, one user mentioned that *“they go*

on long walks which I don't really have time for and Fitbit don't really register bike activity which is what I spend my time doing instead of walking. They also use a stairmaster" (FB5, M36, researcher). This user did not achieve the results needed to reach the goals and felt dissatisfied. The user then reasoned that he could not reach the goals for several reasons, such as the lack of time, inaccurate measurements by the device and lack of equipment, which was also shown in the examples above. The user chose to hold circumstances accountable for the dissatisfactory data, and thus dismissed its validity rather than attempting to change his behavior. As one user put it *"I might rationalize it to myself"* (JB11, 28, female).

6.11.2 Procrastination

The coping tactic of procrastination describes how the user reacts to correct the unsatisfactory data by adopting strategic thinking, which is often followed by making both short-term and long-term plans.

If the user had not reached satisfactory results, the user might start considering the circumstances around it and how to change these accordingly. However, the user tends to procrastinate rather than acting on the considerations. Procrastination is opposed to dismissal where the user automatically placed the blame on the circumstances, and where no aspirations for the future were voiced. Commonly, one user said that it *"makes me think. It does affect me. Makes me think of how I can improve. I would be upset if it would be continuous"* (JB18, F38, researcher). The user reverted to seeking to change the behavior by stating that he or she had thoughts about the future, such as *"I need to move more tomorrow"* (JB11, F28, engineer) or *"I'm thinking then you just pull yourself together tomorrow"* (JB25, M23, student).

The desire to change was sometimes accompanied by a strategic element. By looking to change for the better in the future, the user might go to the data to get an overview of the performance results. The user thus placed the dissatisfactory results in the perspective of past and present. For example, a user shared that *"My behavior becomes slightly strategic when I haven't reached my goal"* (JB6, F29, designer) followed by checking data. Another user described that *"If I don't reach the weekly goal, then I'll go back and look at what I missed and why so I can try*

to change it in the future” (FB8, M41, IT manager). One user mentioned that *“if there are too many days in a week where I don’t make the 10000 steps, I tell myself to go do some sports more often”* (JB5, M29, account manager). However, the user is not necessarily trying to go beyond the preset goal in these considerations about what to do next. One user firmly stated: *“I don’t try to overcompensate, I just want to meet the goal”* (JB14, F30, marketing manager).

However, planning behavior is often intentional and only sporadically leads to execution. A user confessed that *“I have considered whether it wouldn’t be a great idea to taking a little evening walk, when you have not achieved your own goal. But I haven’t really done it yet”* (JB25, M23, student). Another user earnestly shared that even though she aspires to change when she sees bad results, it is more likely *“I will probably deliberately miss my goal, or know I haven’t made it, half of the time. Maybe half of the time I will do something about it. Like twice does aspire a week I will do something about it”* (JB11, 28, female). This suggests that the user seeks to change behavior but does not, though aware of personal procrastination. It is only occasionally that the user might act on the aspirations.

There is a possibility that the procrastination tactic might be more common if the user has practiced it for a longer period of time. One user said that *“you become more relaxed with the measurements over time”* and that *“in the beginning I would go out and take a long walk just to be sure to make the 10 000, and now I am more relaxed about it”* (FB4, F28, researcher). Nevertheless, the same user then aspired to meet the weekly goal average, rather than the daily goal. Another seasoned user stated that while viewing weekly reports of the personal performance he *“would say that for the coming week, you should be more focused on this and this”* (FB7, M28, lawyer) and specify which parts he had been lacking on, in order to behave in a more focused way in the forthcoming week.

6.11.3 Selective attention

The next coping tactic is selective attention, which is when the user only focuses on the goals that they are more likely to achieve, rather than those that are more difficult to attain. This means that the user places emphasis on goals that he or she

believes are important. Most users had some type of favorite performance category, often based on whether they performed well in this category.

One user was particularly fond of her achievements with stairs. She shared that *“I know that I will do well on [stairs]. Stairs are thus important to me. It gives me the boost”* (FB4, F28, researcher). The same user explained that it is *“what I will look at most”*. By applying selective attention as a response, the user can bypass having to address or be exposed to unsatisfactory results, and merely focus on those that are attainable. The user might even adjust the interaction with the interface to abide by selective attention to the favored categories. One user said *“you can switch up what you look at in the dashboard, so you can prioritize and see what you primarily look at up top. That thing with how much I’ve lost and how far from my goal I am, I keep that at the bottom, I don’t even look at that”* (FB2, F40, housewife). The categories that were not viewed often would also be discarded as unreliable. For example, a user said that *“those active minutes, I have a tendency to view them as so so”* (FB1, F26, nutritionist), which indicated that she did not consider this category as important enough to view.

Selective attention also meant that the user might continue to change behavior in order to excel in the category, which reinforced the initial departure point, as well. Another user said, *“as long as I ran instead of lifting, I could measure how much I ran. It ended up being that I would rather run than lift because I wanted the result to look as good as possible on the Jawbone”* (JB10, M29, account manager). Another user observed this change in himself as well, yet argued that *“You could almost always see how you adapted your movement”* (JB3, M29, account manager).

When a user is asked how he reacts to not reaching his goal he says that *“they outweigh each other, my average is well over my daily goal, but there’s some days you do not reach it, and others where you blow it away and nearly quadruples it, or maybe only triples it”* (JB25, M23, student). In this case, the user disregards the results but continues his reasoning by applying selective attention to his overall goal. He does not disregard the information completely, but chooses to place selective attention on the data as a whole or with a long-term perspective.

Social influence is suggested to affect the selective attention of the user, so that the user reverts from the originally favored categories in response to the presence of others. For example, one user shared that *"I have chosen to exclude friends' steps in my dashboard because I felt that I got a stomachache every time I went in to check my stats. I mean, I would compare myself then. I wanted it just to be about me, and my activity and not about others' activity"* (FB1, F26, nutritionist). Another user chose to only include very close social connections because of this. She said *"I don't think I would add people that aren't as close as my mom and boyfriend from my social network. Because it is for me, myself"* (FB4, F28, researcher). Both these examples stress that the user chose to give selective attention to themselves, rather than to others. They both argued that including others would cause them to look at data points that were not originally relevant to them, and then feel unnecessary competition or comparison simply because the social connection was there.

6.11.4 Intentional neglect

The fourth coping tactic is intentional neglect. The user will only review the data if he or she estimates that it is enough to be satisfactory, thus avoiding the process of potentially reacting, reflecting and responding negatively altogether.

The users would check the data when a lot of activity had been carried out. For example, one user expressed that he would check *"every two days. Especially, I check when I do sports. Then I want to see my data, but if I don't do sports I tend to not look at it, because I feel guilty"* about not doing sports (FB7, 28, lawyer). Another user stated that she felt *"Guilty. That is also one of the reasons I haven't been using it lately. I sometimes got upset about the fact that I couldn't always achieve my goal"* (JB12, F27, student). Because of the emotions, like guilt, the user checked the data less often, and often only in relation to activity that was estimated to come closer to a satisfactory goal.

Alternatively, the option of lowering the goal despite repeated nonattainment of a goal was not regarded as a possibility because *"maybe my goal is too high, maybe I should lower it to 9000, but I would feel like a wimp"* (FB5, M35, researcher). On the other hand, some users would not increase the goal because *"I don't want to feel like I don't conquer the new goal. I think it's just my own mental sort of*

thing, that if I create new goals I am not going to achieve them and be disappointed in myself" (JB13, F30, project manager). The user response was to intentionally neglect any possible interactions with the data dashboard, such as making alterations of the goal, to avoid feelings of disappointment or inadequacy due to remembering the reaction and reflection related to recent results.

Intentional neglect also appeared when the user avoided certain parameters of the data because it was rarely or never satisfactory, even though some categories were fulfilled. One user said that calories was neglected at all times because *"I never reach my calorie count even though I go on a 10km run. It never comes up there"* (FB4, F28, researcher). In this case, intentional neglect was closely tied to the coping tactic of selective attention. The user exercised intentional neglect to fulfill a certain performance measure and then exercised selective attention on this performance measurement and ignored others.

The coping tactic of intentional neglect suggests that the user does not adjust his or her behavior to meet the goal, but only tries to validate that his or her perception of behavior is sufficient on occasion. It implies that it is a way for the users to avoid any rejection of the data, which might be considered as distressing and a failure.

6.12 Limitations

In the process of conducting interviews, it is inevitable that one is faced with a possible interviewer bias as the empirical investigation is placed in a subjective and personal sphere. However, identifying and understanding the researcher's involvement in the context and the population will help define the limitations. In this context, I have been exposed to the Quantified Self community through meetings and conferences. I have also tried the devices, both Jawbone UP and Fitbit, in an attempt to understand the users' underlying motivation and interaction with said technology. This might have led to valuable observations that aided the study and the interview guide, but also impaired the possibility of keeping an outsider's reflective perspective. However, we are limited in our ability to understand what is real, so therefore (Mingers et al., 2013), I can only depart from my informed understanding that has accumulated throughout observations in the empirical realm. I attempt to bring transparency by outlining these limitations.

Nevertheless, it should be noted that to avoid a particularly strong immersion in the self-tracking community, I only used the devices for a limited amount of time.

The sample only has participants from a select few countries, primarily in Northern Europe and a few from North America. A more varied population could present more diversified and nuanced results. Furthermore, some participants were not conducting the interview in their native language, which entails some linguistic constraints in sharing their perceptions. Therefore, there is a possibility for future research to perform a discourse analysis that looks further into at the terminology chosen when addressing the self-tracking activities.

The interviewees participated in telephone interviews, which inhibits the level of interaction and might also impair the extent of the response. The participants might become more or less reluctant over the telephone, which could have an impact on the data collected.

6.13 Chapter summary

The study collected 54 in-depth semi-structured interviews with experienced users. Then the general results around use and experience of the devices was presented. The second part of the study results presented a deeper look at the user's reflective process by presenting four steps: review, reaction, reflection and response. The response might be rejection, which in turn leads to the findings of four coping strategies: dismissal, procrastination, selective attention and neglect.

7. DISCUSSION

7.1 Introduction

The proliferation of technological development is influencing everyday life experiences. These developments inspired the aim of this research to gain a deeper understanding of how the advancement of experiential computing is influencing and even transforming our perceptions and experiences as individuals. With technology seeping into everyday life, these everyday tools are increasingly equipped with embedded computing capabilities that allow its user to be ubiquitously monitored throughout these experiences and activities. Not only are we monitored and self-tracking, but in many cases, we also have access to the product, namely the data on ourselves. This personal data is not a new concept, but the access to it provides a unique perspective on our endeavors in everyday life. The personal data offers a new perspective in viewing the experience, analyzing it, gaining awareness and drawing conclusions. In light of this, the research interest is framed by how self-tracking for self-quantification through experiential computing is influencing the user's perception on personal performance.

To summarize this dissertation, the research is based in the field of experiential computing focuses on the mediation of a lived experience between the technology and the user. This research investigates the transformative effect that IT has on the lived experience, by zooming in on the user's perspective, namely the perception and the performance related to experiences. In this understanding, technology is not merely instrumental, but mediates the user's experience in the world to the user. The theoretical lens is drawn from behavioral economics, where the focus is placed on the dual system attributes and shortcomings in the form of cognitive biases and heuristics. A mixed method approach was used to conduct a field study of new users of self-tracking as well as an interview study with experienced self-tracking users.

This research further specifies the understanding of how experiential computing influences users in an everyday context by conducting empirical studies of both new users and experienced users. This gives insight into perceptions and performance both in the introductory phase as well as at a later. It highlights the

complexity of self-tracking activities through such devices, and thus brings out the everyday aspects of technology.

In this chapter, the findings are discussed in relation to the literature in the emerging field of experiential computing and the related self-tracking activity.

The findings aid in specifying and supporting Yoo's (2010) schematic framework of experiential computing that positions a lived experience within four dimensions: space, time, actor and artifact. On the basis of the findings of this dissertation, a specified framework is proposed as a conceptualization of the relationship between the user and the self-tracking device. The conceptualization offers a further understanding of how and why the relationship between the user and the self-tracking device transforms the experience. The process thus addresses an overall view of the experience of experiential computing by engaging in self-tracking activity.

Within the transformative process identified through using experiential computing, the focus is then placed on the engagement after exposure to personal data. Here, the activity is also understood as a process where the user experience can be analytically captured in a process model such as review, react, reflect and response. The engagement and reflection is assumed to be particularly challenging, and the behavioral economics perspective provides useful as it aids in explanation of why and how the relationship between the device and user transforms the experience. More specifically, the engagement leads to that certain cognitive processes are spurred by system 1, and invites several theoretical concepts from behavioral economics to understand the engagement of review, react, reflect and response.

The chapter is structured as follows. The first section presents an elaboration of the findings of the two studies and how these contribute to the understanding of the role of technology in everyday experiences. The findings are then discussed against the theoretical background. Then the discussion turns to experiential computing to discuss the user device relationship. By narrowing in on engagement within this relationship, the discussion proceeds to focus on the self-tracking activity and the challenges related to such engagement. Finally, the implications for practice and research are presented.

7.2 Reflections on the findings

The research interest was framed in the theoretical background as five components that make up the self-tracking experience. The five components are the information technology (experiential computing), the activity (self-tracking), the product (a personal data archive), participation (data engagement) and outcome (data reflection). These components are separated for the purposes of clarity in this text, but are deeply intertwined with each other throughout the activity.

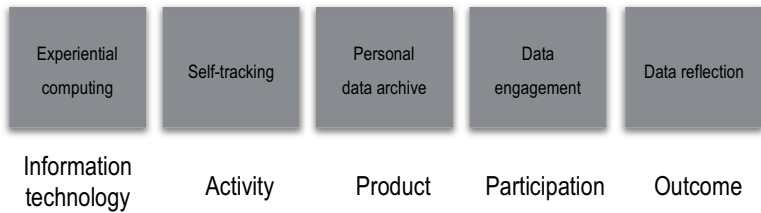


Figure 11. Components of the activity of self-tracking

This dissertation studies how the user uses a self-tracking device for self-quantification and how it influences the perception of personal performance. Thus, the adoption of experiential computing for self-tracking activities was the catalyst for the data collection and lead to observations related to what happens after the exposure to data, namely a complex process of data engagement and data reflection commences. The data engagement consists of participation with the available data, such as checking the data, changing the goal, and acting on notifications but also participating with social elements. Through engagement, the user is likely to be spurred to reflect on the data. The reflection is highly subjective and is influenced by varying level of engagement. Due to the prominence of these findings in these components in the data collection, participation and outcome are revisited and discussed in this chapter.

Initially, the outcome component was labeled as self-reflection but this has now been updated to data reflection after conducting the two studies. The reason behind this is because after exposure to the personal archive, the user did not necessarily reflect on the self, but rather the meaning of the data. This might have

involved whether the data was probable and satisfactory and only after this was there a possibility that the user engaged in self-reflection based on the awareness gained. As a result, the outcome is then considered to be data reflection, which might include elements of self-reflection. The data reflection is to consider the data as a whole.

This section explores the findings on the influence of self-tracking on the user's perception in relation to the theoretical background. Afterwards, the influence of engagement and reflection on self-tracking is then examined more specifically through the perspectives of behavioral economics and experiential computing. Behavioral economics sheds light on what occurs in cognitive processes during engagement and reflection while experiential computing offers a view on how the user's experience is framed and transformed through engagement and reflection on the data.

7.2.1 Data engagement

The engagement with the data means that the user participates and sometimes interacts with the data that is exposed through the device and data dashboard. The engagement with data is underlined as an important component of optimizing the personal performance measures in the self-tracking activity (e.g. Blum, Pentland, & Tröster, 2006; Hultgren, Wiggers, & Jonker, 2014; Khovanskaya, Baumer, Cosley, Volda, & Gay, 2013). It is important as it strengthens the user's relationship to the personal data, especially by including input and experimentation (Consolvo et al., 2008; Jain, 2003). At the same time, getting users to actually engage with the data is the primary challenge identified in the theoretical background. As the findings of this dissertation are scrutinized among previous studies, it is suggested that engagement is evident in the early stage of use, but simmers down over time.

In this dissertation, the engagement measures that were collected were primarily focused on checking the data, changing the goals and notifications, but also social elements.

7.2.1.1 Checking the data

The users would check the data intensively in the beginning but then it declined over time. The users argued that during the initial period, they were curious about their patterns and therefore checked often. Already in the second and third week, there was a measured and self-perceived decline in checking data. Although, when it came to the routines of checking the data, the users in both studies said that they would often initially check the personal data in the morning to view the sleep results and then check again at night for the step results. This indicates that the users would check when they knew there were results, rather than looking at partial results or progress.

When asked why engagement was not as intense as the start, the users claimed they had gotten a sufficient understanding of the data and did not need to check it as often nor did it have equal interest. The new users said that the motivation decreased because the technology became less interesting; thus they were less intrigued by the idea of checking the data. This is consistent with the engagement of experienced users, who eventually could go several days without checking and thus checked only to get an overview of the time passed, rather than attempting to chase the daily goals. This suggests that the novelty of the information decreased over time. Nevertheless, the first study showed that new users' step performance was positively associated with checking the app, which means that the more the user checked the app, the greater the step performance. However, the results did not necessarily decline over time, but that daily performance measures were simply not as important as the overview was.

As suggested by other studies (Bell & Gemmell, 2007; Gemmell et al., 2006), the user might then perceive the data collection as a personal archive rather than a daily performance log. The personal archive is thus used to be able to retrieve data, when needed. Although, it is not necessarily used as a tool for memory aid of events as it is a tool for understanding and reflecting over personal performance over time (Bentley et al., 2013). As proposed by Fitzgibbon and Reiter (2003), the engagement with the personal data may thus be considered a self-management tool, as it gives awareness, that might lead to insights (E. K. Choe et al., 2014) and inspire behavioral change (J. J. Lin et al., 2006). In this respect, the user gains awareness and insight about everyday performance in the initial period which is then approached as a personal archive over time. Therefore, the purposes of the

personal data seem to shift from daily self-insight to getting an overview of the self.

However, unlike the step related performance, checking the data was negatively associated with the sleep performance. This means that the more the new users checked, the less likely they were to improve the sleep performance. Some of the new users described that checking the sleep data could be frustrating and brought forward negative emotions that implied they felt pressure when the results were unsatisfactory. The checking and exposure to data may then work as a stressor that disrupts the sleep which causes “racing thoughts and thus made it difficult to fall asleep” (Choe, Consolvo, Watson, & Kientz, 2011, p.3057). The stressor might arise from the thought concerning the inability to alter the sleep data and behavior. The experienced users did not express the same discontent from being exposed to the sleep data. They primarily highlighted their interest in viewing the data as a source of awareness and insight into sleeping patterns. The only criticism towards the sleep data was that it might not be accurate and that the device was troublesome to wear while sleeping.

7.2.1.2 Changing goals

Another engagement activity was changing the goals. The users would rarely change the goals and when they did, it was primarily upwards rather than downwards, making it harder to reach the step performance. This occurred in both studies. Although among new users, changing the goals did not have a significant relationship to sleep performance. The users explained that increasing the goal was done because the initial goal was too easy and also to motivate them to walk more. A select few even admitted that a goal that was easily attained made the user lazy over time, thus increasing it was beneficial. However, the users hesitated to change the goals downwards because it was considered an admission of some kind of defeat. Nevertheless, the few times it was done among experienced users it was to allow the goal to be reached more often, because it was demotivating to continuously achieve unsatisfactory results. The goals of other users were not mentioned in either of the studies. The users would thus only react to the performance results of other users and use this as a point of comparison. It was not interesting to them whether the other user had reached his or her goal.

In the literature, the goal is positioned as a concrete challenge for the user, which will spur motivation to reach the goal and as such, change behavior accordingly (Consolvo, Klasnja, et al., 2009; J. J. Lin et al., 2006). However, while the goal may have a positive effect in the early stages of using a self-tracking device, the goal seems to have a diminishing motivation effect over time. Much like the engagement through checking the personal data, the user started paying less attention to the immediate goal and focused on a larger overview of the results in relation to the goal. The goal still had an important role while viewing the data, but the fact that the goal was rarely changed indicates that it served as an anchor that the user was hesitant to change.

7.2.1.3 Notifications

Also, the notifications were a feature enabling engagement. Notifications works as triggers to get the user to do something (Cosley et al., 2012; Fogg, 2009). For example, status bar reminder in the smartphone are more effective than push notifications or text messages (Bentley et al., 2013). In these studies, the notifications, or triggers, are suggested to be initially useful but the impact fades as the user gets used to them. In this study context, the notifications were sent by self-tracking device's software to the users are meant to act as reminders of the step and sleep goal. In the first study, the notifications had no association with sleep performance, yet a negative influence on the step performance of new users. As the new users described their perceptions, they initially had positive reactions, such as attempting or aspiring to walk more upon engagement with a notification. However, the users also argued that they were not able to act immediately on the notification because they were working or studying, which implies that the notification did not have the intended effect of immediate urgency. In the second study the experienced users described the notifications as well-used and valuable. Nevertheless, over time, the notifications were considered a disturbance and thus ignored or turned off. These findings indicate that while the users might initially react to the notification, only occasional behavioral changes were made and over time, the user ignored the notification. This is indicative of coping tactics such as dismiss and procrastination. Similarly to checking the data and changing the goals, the notifications served a purpose in the beginning, but over time the users became prone to ignore them. The use of notifications can be effective, but depending on the format that they are pushed to the user (Bentley et al., 2013).

7.2.1.4 Social elements

Social element is another type of engagement that offers a possibility for the self-tracking user to share personal data and taking part of others' data. In this dissertation, social elements are shown to have an influence on the users performance and perception. In the first study, social connections were positively associated with both step and sleep performance. Overall, the users expressed interest in the possibility of comparing the data of others to the personal data, but also spurred competition. However, many of the users did not have the opportunity to try this feature, since they did not know anyone to add on. Instead, they reflected on the possibility and considered it as a primarily positive addition for the purposes of comparison and competition; they thought it would give them motivation to perform better. The second study's findings are similar to the first study, where users are noticeably positive towards the social function as it provides a possibility for comparison and competition. They also argued that the comparative setting allowed for more reflection. It was also a fun feature because it was possible to interact and give feedback to others. Still, a select few in both studies were negatively positioned with regard to the social functions. They were hesitant and claimed that the data was too private or that they did not see the value of such a feature for the self-tracking experience. Among experienced users, some even argued that it was a source of negative energy due to the inevitability of revealing the data for others to compare. Due to this, some users opted out of the social function and focused on standalone performance.

In several other studies, the social element, such as exposure to others data is argued to motivate the user by engaging in comparison and competition. The motivation stems in the attempt to gain social approval and desirability (Adams et al., 2005; Tajfel, 2010). In a self-tracking context, the influence of social elements causes self-reflection, which can ultimately lead to behavioral changes because it causes mindfulness of the personal performance in comparison to others (Froehlich, 2011; J. J. Lin et al., 2006). The social elements can thus influence the user's perception but also continue to spill over to performance, such as behavioral change (Ploderer et al., 2014).

The literature indicate that social elements have a valuable role in the shaping of self-perception and this dissertation's findings assume that it also is the case when it comes to the experience of self-tracking, which can ultimately lead to performance change.

7.2.2 Data reflection

After engagement with the data, device and social elements, then the outcome, or data reflection, is likely to take place. The reflection is related to how the user perceives the data in relation to the initial experience and thus, it is a complex and highly nuanced area of discussion. This section is thus divided into a main theme (meaning of data) and a related topic that emerged during the interviews, trust and transparency. Finally, the coping tactics are briefly mentioned as a type of reflection that occurs, and are then elaborated further in the subsequent behavioral economics section.

7.2.2.1 The meaning of data

The exposure to personal data led to individual interpretations, yet with the prevailing reaction was to gain increased personal awareness. The study's users argued that the more data available, the more they got out of using the experiential tools. At the same time, not all of the personal data was considered to be relevant for everyday use, but users enjoyed knowing it was there, should it be needed for future reference. In the beginning of the adoption period, the users were intrigued by the data. A majority of the users said that they started by checking the data daily, but then that decreased to only few times per week, if not only once a week to view weekly averages. This is similar to the discussion about engagement where the users perceived that the awareness changed over time, as it became less fascinating after a while. Therefore, the new users expressed great interest in the initial period but underlined that it declined over the duration of the 21 or more days that they used it. The experienced users also shared that they had gained awareness in the initial period, which was one of the reasons for them to continue wearing the device. The continued use also suggests that the data collection itself became a habit, although they did not engage with it every day.

These findings are consistent with studies on other experiential devices, such as the smartphone (Karapanos, 2013), where the novelty decreased as the device had grown to be an integral part of everyday life where experimentation and exploration has ceased (Bødker et al., 2014). There was, however, a differentiation between new and experienced users. The new users shared that the exposure to data also inspired a wish to further analyze and experiment with the personal data. This resulted in making comparisons and identifying patterns. The experienced users did not emphasize this activity, and argued that they already had identified patterns and therefore did not regularly seek new discoveries in the data. Instead, they rather used it as a swift checkpoint for personal performance in everyday life. The possibilities for experimentation were thus more interesting to the new users than the experienced users. The value of experimentation is emphasized by Jain (2003) that assert that the data and accompanying visualization should aid the user to explore the perceptions of the data, yet this noticeably changes over time.

Both new and experienced users agreed that the gained awareness lead to insights, but also to behavioral change. Experienced users shared the perspective that it was a way to be held accountable for any possible deviations and helped to maintain behavior, which is also underlined in other studies about using activity monitors (J. J. Lin et al., 2006). Nevertheless, the experienced users were also more inclined to not follow the notifications and to deviate from following the set daily goals (Bentley et al., 2013), as discussed in relation to the coping tactics. The new users were more enthusiastic about the prospects for maintaining the behavioral changes in the now, while the experienced users focused on the possible long-term effects of being active.

Moreover, the personal data was a type of personification and a picture of health according to the experienced users. Yoo (2010) argues that data gathered through experiential computing devices are indeed embodiment of the user, rather than representational. The users of the studies in this study did not see the data as external to themselves but as a manifestation of their activity. It was not argued to be a representation, but rather an intimate account of a real aspect of life. This was despite that they recognized that errors could be made by technology. Notably, the new users were not equally as specific in their description of the data but agreed that it was a type of diary about their body. Most of the users from both studies suggested the data was a type of embodiment of the personal performance during a

lived experience. Despite the fact that new versus experienced users had varying degrees of attachment to the data, the attachment was present in the narratives and shared commentary. The experienced users had a longer relationship to the personal data than the new users, which might be the reason why they also expressed a stronger relationship. The discussion of personification and embodiment indicates that the users had an emotional attachment to the personal data, rather than it just being a tool for rationalization and activity optimization. It was particularly noticeable when the user told stories of when the device had been forgotten at home and thus not worn. In these circumstances, the user felt distress as the data was not collected and as if any activity was then purposeless, because it was not captured.

7.2.2.2 Trust in data

Both new and experienced users said that they trusted the data, yet acknowledged that there was wiggle room for error. This means that the users trusted the technology to embody the experience in its general understanding, but that there might be error in the detailed information. This room for error brought forward some skepticism, yet as an overall experience, there was trust for the data. The users also expected that the accuracy of data would improve, as the development of device features improved over time. According to Jaimes, Murray, and Raij (2013), the trust is maintained even though there is inaccuracy. The issue then resides in that the system does not help the user understand the errors possible in the data which might have implications in the long run (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003).

When it came to the different types of data and trust, the new users of the first study trusted sleep data slightly more than step data. However, the difference in averages was very small. The experienced users of the second study exhibited the same pattern, and assumed that it was trustworthy, yet with reservations and skepticism towards the details. Some argued that the lack of trust was because they did not know how the technology was working. However, during the post-interviews, the new users voiced more assertive statements and skepticism than the experienced users. This might be because the first study's users were not users by their own choice, whereas the experienced users were. Despite the issues of trust, the users wanted to continue using the device.

7.2.2.3 Reflection to rejection

The examination of what occurs during data reflection brought light to the coping tactics that were discovered among the experienced users. There were also traces of the coping tactics among new users. For example, new users initially responded to the notifications by adapting their behavior, but after a while, they started ignoring them and justifying it with dismissal and procrastination, and maybe even intentional neglect. However, the coping tactics were not as apparent among new users as they were among experienced users. In the first study, the self-tracking device operates as a commitment device which suggests that system 2 was present. In the second study, the users had used the self-tracking device for a longer period of time and no longer treated it as a commitment device. Instead, the users had developed coping tactics that suggests a more automatic behavior such as that produced by system 1. The findings suggest that the new users and experienced users were different in the approach to the meaning of data and the awareness of the data.

The self-tracking activity and its relationship to the dual system and the coping tactics are further elaborated in a forthcoming section (7.3).

7.3 Self-tracking and behavioral economics

Behavioral economics is a theoretical perspective that opens up the possibility to investigate how cognitive processes during the data engagement and data reflection informs the user's perception of personal performance. This section incorporates the findings and discusses it from a behavioral economics perspective. This is done by conceptualizing the steps of the engagement and reflection stage then discussing the dual systems involvement.

The user goes through several steps after the exposure to data, as presented in the second study. More specifically, the user is reviewing data, reacting to data, reflecting on data and responding to data. The finding of these steps suggests that exposure to data generates a process that is built on several stages of engagement and reflections, which are identified as review, react, reflect and respond.

These steps are proposed to be an extension to the previously presented models that revolved around reflection after exposure, as presented by Karapanos (2013), Li, Dey, and Forlizzi (2010), Pirzadeh, He, and Stolterman (2013) and Verbert, Duval, Klerkx, Govaerts, and Santos (2013). The mentioned models emphasizes reflection as one unified stage, yet take little consideration of the complexity and possible steps of what occurs during reflection. For example, they do not explicitly distinguish between what happens in the case of exposure to satisfactory versus unsatisfactory data. The findings of this dissertation present an alternative perspective of viewing the reflective stage, namely by identifying reflection as a process that incorporates different steps.

Moreover, another finding according to the data collection is that the reflection may lead to a rejection response, which means that the user rejects the data. The rejection leads to using coping tactics to deal with the exposure to unsatisfactory data. In the previous models mentioned, the reflection stage is followed by some sort of action (Li et al., 2010), new perspective (Pirzadeh et al., 2013), new meaning (Verbert, Duval, Klerkx, Govaerts, and Santos, 2013) or identification (Karapanos, 2013). These outcomes are general and thus do not address what might occur when the data is satisfactory or unsatisfactory in that causes displeasure for the user. Therefore, the findings of this dissertation suggest that there can be satisfactory or unsatisfactory response to the reflection, which leads to alternative outcomes.

The figure below illustrates the steps of the reflective stage that the user goes through.



Figure 12. The steps of the reflection stage during a self-tracking process

These are the steps that occur from the point at which the user is exposed to personal data and continues to engage and reflect with this data. The exposure leads to an immediate reaction, subsequent reflection and finally the response. The

first stage is review and occurs after the user is presented with personal data in the software. The data is then quickly reviewed through a scan of the data dashboard. The second stage is reaction and occurs instantaneously once the user has been exposed to the personal data. The reaction is emotionally grounded and is quite subtle and brief. The third stage is reflection, by absorbing and considering the data. This does not necessarily have to be a lengthy process, but can merely be to place the data in context and make a quick evaluation of it. The last step is response, where the user decides if and how to act on the personal data. The studies suggested that system 1 has a strong presence throughout the process, as users swiftly proceed through the data. Even in the reflection stage, the evaluation is neither effortful nor includes a deeper analysis, but remains rather swift and intuitive based on the data. Any lengthier analysis or exploration mainly occurred in the beginning, as is common when adopting experiential computing devices (Bødker et al., 2014; Karapanos, 2013). The process ultimately leads to a response. If the results are satisfactory, there is a non-response, which means that the user closes the mobile app, and resumes to their status quo presence in everyday life. If the response is that the data is unsatisfactory, then rejection occurs. In relation to rejection, the coping tactics appear.

The findings lead to conclude that the self-tracking device does not function as a commitment device, but is a re-focusing tool that summons coping tactics (Mimmi Sjöklint et al., 2015). The coping tactics are mechanisms that the users adopt because they want to maintain a status quo and circumvent the potential or actual experience of failure, when exposed to unsatisfactory data. The coping tactics are primarily related to system 1, the swift and intuitive cognitive process. The findings also show that very few users take the time to engage in longer and more elaborate reflection when viewing personal data, especially when it comes to experienced users. This is likely because it is challenging and takes more cognitive power to explore with system 2. Therefore, it is rare that the user makes the effort to go through this process, but merely proceeds with the coping tactics, instead. The assumption that the dual system exists allows discussion on contrasting perspectives of the commitment devices versus the emergence of the coping tactics. More specifically, the theoretical framework of the dual system is a lens that is used in the study to provide understanding of how the user is exposed and interacts with the personal data. The dual system is present when reflecting on personal data and lingers between the rational and intuitive systems. The

application of this system in various self-tracking scenarios is used to discuss the emergence and maintenance of reactions related to personal data.

7.3.1 Commitment device

The self-tracking device may operate as a commitment device for new users in the first period of adoption, but did not seem to have the same effect on experienced users. A commitment device is meant to be a reminder or a trigger to help the user overcome irrational behavior and act more deliberately and consciously (Ariely & Wertenbroch, 2002). It is thus a preventative measure that helps the user do what they should, rather than what they want (Milkman et al., 2008).

In terms of the new users, the function of a commitment device might have been reinforced by the contextual factors. In this case, taking part in a field study might have imposed a sense of consciousness on the users to check the data regularly, especially since the field study was limited in duration and thus the users only had a limited amount of time to gain the advantages of using a self-tracking device. Moreover, the new user is likely to be more engaged with the device in the newer phase of adoption (Bødker et al., 2014; Karapanos, 2013; J. J. Lin et al., 2006). In contrast, the second study involved experienced users who have independently chosen to adopt the self-tracking device. These users exhibited awareness of the personal data, yet at the same time, did not adopt the self-tracking device as a commitment device. There can be several reasons behind this, such as that the experienced user does not feel the limitations of time as the field study users. It may also be that over time, the user becomes more relaxed in his or her relationship to the data, as suggested in the findings surrounding engagement, like checking the data, changing goals, and notifications.

The study of the experienced self-trackers led to findings that suggest the self-tracking device is not a traditional commitment device. Instead, the observations of experienced users showed that they often respond to the data by scanning it quickly without a behavioral response, or rejecting it through adopting coping tactics. Both accepting and rejecting was swift and infers that the user relies on quick, intuitive and emotional reactions spurred by system 1 when exposed to unsatisfactory data. This is as opposed to engaging a more effortful, controlled and logical part of the dual system to analyze the data. This suggests that the

experienced user applies system 1 as a way to interpret data, which in turn leads to often shallow and intuitive results that might just confirm the user's original departure point. The data thus shows that the experienced user is less likely to be influenced by the self-tracking device as a commitment device.

Indeed, the system 1 was noticeably present when going through the stages after exposure to data that was unsatisfactory, which is another testament to that self-tracking device did not work as a commitment device in a particular setting. In the reflective stages, many users jointly revealed that they had gained awareness, sometimes changed behavior and adopted a different lifestyle upon using an activity tracker. Yet, when inquiring further about these adopted patterns and questions related to the goals and results, it was revealed that when exposed to unsatisfactory data, the stages of reflective process did not necessarily lead to effortful reflections, but only allowed a swift and emotional course to occur. The stages were also consistent with review, reaction, reflecting and response to the personal data. In actuality, the user quickly dismissed the data and did not make an effort to change behavior to attain the preset goals. Instead, the user seemed to adhere to a swift procedure that allowed a quick rundown of the data followed by reverting to an unchanging behavior using the coping tactics. Therefore, on the basis of these findings there is reason to assume that the self-tracking device does not act as a commitment device, as this is supposed to entice a more deliberate and conscious behavior (Milkman et al., 2008). The users had gained the perception of deliberate and conscious behavior, but exhibited a clear inability to abide by the commitment device. Instead, the reaction and response witnessed an irrational and emotionally bounded result, such as not viewing the data, ignoring bad results and only paying attention to positive results.

In summary, the inability for the commitment device to work as theoretically assumed might be due to the user's relationship with the self-tracking device evolves over time where. As mentioned previously, the new user is initially influenced by the commitment device but over time the relationship to the technology changes as the users get more used to it in everyday activities, which leads to less influence. Based on the findings in the two studies, there is an indication that the changing relationship leads to that the user starts to use coping tactics to interpret the data, rather than using it as a commitment device.

7.3.2 Coping tactics

The coping tactics indicate that self-tracking users are prone to adopt heuristics when viewing personal data, instead of a rational perspective as prompted by a commitment device. In the attempt to try to understand the origin of these coping tactics, the dual system is a foundational basis by which cognitive processes are discussed. The first study gave strong indications that the perceptions of the data did not match the performance of the new users. This means that the new users focused on certain aspects of the data that were successful, rather than those that were less satisfactory. In the second study, the thematic analysis leading to the coping tactics emphasizes an inevitable contrast and conflicts that arise in the dual system when analyzing personal data. Thus, the contrasting nature of user's perception about personal performance arose in both studies but to various degrees. From this angle, it seems plausible that the coping tactics are present from an early stage, but are more prominent as the user becomes more experienced. When reviewing the coping tactics, it is suggested that the dual system's system 1 is predominantly used.

The identification of the coping tactics suggests that it is painful for the user to be exposed to unsatisfactory data. However, the existence of such coping tactics actually indicates the contradictory idea — that the user attempts to make the experience as pleasant and painless as possible. The coping tactics are thus a means to encounter less pain despite unsatisfactory results. Therefore, the coping tactics are argued to be rooted in loss aversion, which is an inherent part of the human state (Kahneman et al., 1991). Because of loss aversion, the user is inherently afraid of experiencing loss and therefore attempts to avoid it. The loss is perceived as painful, more painful than the equivalent gain (Kahneman et al., 1991). As a result, with the help of the swift and subconscious system 1, the user develops mechanisms, i.e. coping tactics, to prevent and outmaneuver the eventuality of pain. The coping tactics not only support system 1 but confirm the presence of other heuristics and biases, such as status quo bias and availability.

The most common coping tactic, dismissal, ensures that the user takes no account of the data when being exposed to it and proceeds to not acknowledge the unsatisfactory meaning of the results, both details as well as the whole. Instead, the user resorts to various types of arguments that generally justify the inability to accomplish the goal placed by the user in relation to the self-tracking device. For

example, the user sees that he has not reached the sleep goal and dismisses this because his girlfriend was sleeping over, because he knows this disturbs his deep sleep as well as duration. However, the user does not consider to make the adjustment to go to bed earlier even though he knows the results are affected by the circumstances. In this way, the user justifies the unattained goal. During dismissal, the user is experiencing potential failure through unsatisfactory results mediated by the data. Because the user is averse to loss, he or she diverts the sense of failure by dismissal the data. Much like loss aversion is painful, several of the users from both studies voiced the feeling that it was emotionally more charged experience to not reach a goal than to reach it. The reaction is due to that the user experiences loss aversion. The self-tracking setting shows that this can occur, even when the failure is self-imposed and as such constructed by the context of wearing a self-tracking device. This means that the user experiences failure even though he or she has chosen to wear the device and chosen to set the goal, which can also be changed at any time. Despite the fact that the goal is self-imposed through adopting a device and a goal, the user exhibits an unwillingness to change that goal, especially downward as shown in both studies. Similarly, the user who had a lower goal from the beginning may moderately adjust it upwards, although this was rarely done. This suggests that the goal works as an anchor to the user (Frederick et al., 2010). An anchor is causing a bias towards an initial value, even though it might not be relevant for the setting. Thus a random number, such as the goal, act as a reference point for the individual (Ariely et al., 2006). The dismissal is thus activated by the user's feelings of loss aversion, due to that the goal is an anchor.

The coping tactic, procrastination, is also driven by loss aversion. Yet, unlike dismissal, procrastination is owing to the fact that the user has a status quo bias, namely the attempt to maintain a neutral state where loss is avoided (Kahneman et al., 1991). Procrastination thus occurs when the user sees unsatisfactory data and summons a desire to correct the insufficient behavior. The aspiration is accomplished by adopting short-term and long-term plans. The scheduling of plans might suggest that system 2 was involved, yet the users described the planning as a reaction. For example, the user saw that he had not reached the daily 10 000 goal and the immediate reaction was to impose the response that the daily average would be satisfactory when seen on a weekly basis. However, the intention to do something difference the next day was rarely fulfilled. Thus, the

user attempted to achieve a mental status quo, where the neutral state was the weekly average rather than a daily average. Thus, the procrastination occurs because the user perceives the inability to reach the goal as a failure and attempts to correct it because of a status quo bias. Similarly to dismissal, the intent to reach the goal also suggests that the user considers it as an anchor. The user sees the goal as a numerical reference point, even though it might not necessarily be relevant for the context.

The coping tactic, selective attention, means that the user places emphasis on data that he or she is more likely to achieve, rather than on goals that are more difficult to attain. This means that the user pays attention to selective parts of the data during exposure. Selective attention is also due to loss aversion, where the achievable goals are enhanced as superior to the ones that are unachievable. There is a reluctance to part with the unachievable goals, because there is pain related to giving it up by failing (Tversky & Kahneman, 1991). The unachievable goals are thus not enhanced. Instead, the unsatisfactory results are ignored so that the user does not have to experience the sense of failure. For example, the user checks the number of stairs climbed or deep sleep hours slept, because the user knows that he or she performs well in these categories. The data that is of interest becomes the anchor that guides the experience. This also indicates that anchoring (Frederick et al., 2010) is an important influencer on perception in a self-tracking context, and is used to extend the realm so as not to experience loss. Thus the new anchor, for example, flights of stairs per day, is not grabbed out of thin air but derives from the existing information available in the environment.

The coping tactic, intentional neglect, means that the user completely ignores checking the data under certain periods of time. The exposure to unsatisfactory data is considered to be so potentially painful to the user that the intuitive reaction is to not look at it at all. Therefore, the user only commits to exposure of data that corresponds to satisfactory data that lets the user retain the preferred the neutral state, and caters to the status quo bias (Kahneman et al., 1991). For example, the user will only check the data after he or she has played a football match or had a very long walk because then he or she knows that there is satisfactory data available. As opposed to selective attention, intentional neglect means that the user does not check the data at all until the user is certain that there is data available to satisfy the goal. Moreover, intentional neglect allows the user

to adopt the availability heuristic (Tversky & Kahneman, 1973), which means that she or he can rely on the latest piece of information that comes to mind to make an evaluation of the experience. The user thus intentionally neglects to open the app and review the personal data and instead relies on past satisfactory memories, rather than being exposed to a loss. For example, the user checks the data after having played a game of friendly football because he knows that this activity accumulates a lot of steps. Rightfully so, the user finds that the step count is more than 12000. The user then refrains from checking the data daily, and relies on the memory of having performed well while avoiding disappointment and the pain of loss.

7.4.3 Social elements

The role of social elements on the user's step and sleep difference is important both in the first and second study. This suggests that the user is influenced by other's presence as well as the exposure to their data, which invites new information that expands the experience of self-tracking but also becomes a benchmark for comparison. Individual performance is thus affected by the incorporation of social elements, such as feeling social pressure (Wogalter et al., 1989). It provides a normative influence where individuals strive to be accepted (Aaronson et al., 1994).

In this study, the social elements had a twofold influence on the adoption of coping tactics. On one hand, social elements enforce the role of the self-tracking device where the users do not adopt coping tactics. The self-tracking is thus a commitment device by exercising some kind of social pressure. This means that having a social network included in self-tracking practices may trigger the user to act more deliberately (Ariely & Wertenbroch, 2002) to gain social acceptance. For example, the user sees data from other users and is spurred to accumulate results that match or overreach the other users' corresponding results. In this scenario, the user is likely to be checking the data more consciously and performs some kind of analysis by comparing it to other users. Such engagement and reflection requires more processing power, and therefore the slower; more effortful and analytical system 2 is working. The social context may spur the user to compare and contrast personal results to others. If the user is performing less than the other users, s/he might alter behavior to try to perform better. Several uses in both the studies stated

that they would like to have other users because this would invite friendly competition.

On the other hand, the existence of a social network and its actors might amplify the coping tactics because of feeling social anxiety. The user might not achieve as good or desirable results compared to others in the social network and therefore resort to coping tactics to abstain from a perceived loss. For example, user A dismisses when s/he sees that user B has performed better by arguing that it was not possible to achieve the same results because user A works longer hours. Alternatively, user A might apply procrastination, attempting at gaining a strong weekly average, to match user B better performance. The user then attempts to correct the insufficient activity by aiming for a weekly or monthly average that is comparable to those performing better on a daily basis. Moreover, the user might apply selective attention to only look at measures that are better than other users. Then again, the user might choose to completely neglect the data to avoid perceived loss, only to check it when s/he is knowingly particularly productive and is likely to excel over others in the network.

The findings thus suggest that social elements can be influential in relation to improving the performance both in terms of steps and sleep. However, the perceptions about the influence of social connections varies from being positive to achieve greater performance differences, which was shown among new users, whereas several experienced users also indicated that it might have a negative influence on self-perception.

7.4 Self-tracking and experiential computing

The perspective of experiential computing aids the understanding of the influence of self-tracking on the user perception about personal performance in everyday experiences. It allows a discussion that focuses on the user's experience and the dimensions that frame it. The discussion departs from the assumption that an experience is the "consequence of interactions between a subject and the world" (Yoo 2010, p.219). The interactions are of particular interest because they can be captured by experiential computing, such as a self-tracking device. Through such capture, the interactions are the activities of the lived experience that technology

can mediate to the user through exposure to data, which leads to data engagement and data reflection. The findings of this study suggest that the mediation influences the user’s perception of the experience.

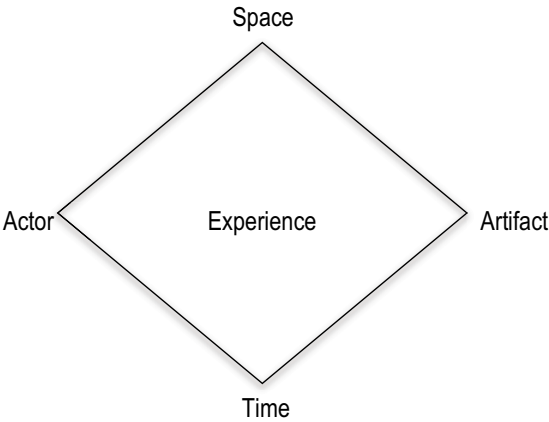


Figure 13. Yoo’s schematic framework of experiential computing.

This discussion proposes that the conceptualization of the embodied relationship between the user and technology should be further specified. The theoretical conceptualization stems from Yoo’s (2010) framework (see figure 13) for understanding the lived experience through four dimensions: space, time, actor and artifact. The dimensions are useful to understand how they contribute to the perceptions of a lived experience of a user. However, the current framework does not fully address how the initial experience may be transformed after the user engages with the personal data mediated by information technology. In other words, the framework accounts for how the initial experience is framed through the dimensions, but does not thoroughly elaborate on how the mediation by the technology influences, transforms or even distorts the perception of the initial lived experience.

When analyzing the findings of this dissertation, the data suggests that technology presence in the initial experience but also technology’s mediation of the initial

experience in a new visual expression can contribute to transform the experience itself. This means that the incorporation of experiential computing, such as self-trackers, that capture and mediate an experience may add further complexity than what is revealed in original model. The complexity was identified by incorporation of behavioral economics that highlighted the cognitive processes that occur in relation to technology's presence, capture and mediation of experience back to the user. For example, the experience of using a self-tracking device involves that the user has to set a goal, such as walking 10 000 steps or sleeping 8 hours per night. These goals are anchors. The anchor is used by the user to compare the initial and lived experience to the mediated experience that is presented through technology. It might be that the comparison between these experiences do or do not match, which in turn brings forward different reactions. Therefore, the initial experience may change through using experiential computing because it brings forward an alternative perspective. Experiential computing thus has an influence on the user, as compared to if the user was not wearing a self-tracking device. Thus, the data concludes that there is an initial experience that is lived and then there is a mediated experience that manifests through exposure to the data captured by the use of experiential computing. The distinction between these two types of experiences was observed in the studies through the engagement and reflections of respondents and suggests a more complex relationship between users and the device.

For example, a user might have perceived he slept poorly, but was then positively surprised when the data showed that he had gotten more sleep than originally and intuitively estimated. The same occurrence could occur in the opposite manner; the data showed that he had slept less than he initially and intuitively estimated. In the first scenario, the user is pleased whereas in the second scenario, the user is displeased. Firstly, the mere presence of the device and its experiential capabilities influences the user, as he knows it is gathering the data. This might lead to him going to bed earlier to achieve the goal. Secondly, the embodiment of the experience brings forward data that influences the initial experience, either in a positive or negative manner. The capture and mediation thus influences the experience in another way where the perception of the experience changes overall. As a result, the four dimensions not only frame the initial experience, but they are captured so that the experience may be re-called and reshaped. However, the data showed that in the beginning the users were very aware of wearing the self-

tracking device, whereas over time, they noticed it less and less. As such, the influence of the self-tracking device is stronger in the beginning (among new users) than it is over time (among experienced users). This means that the degree of influence of the mediated experience may vary among users over time.

On the basis of these findings, this dissertation’s findings propose that the schematic framework of experiential computing should be further specified. The figure below includes bi-directional arrows that represent the presence and influence of experiential computing on the user’s experience because it is able to capture and mediate the initial experience. The framework is originally named the schematic framework of experiential computing, as suggested by Yoo (2010), and will be referred to as the framework in the text that follows.

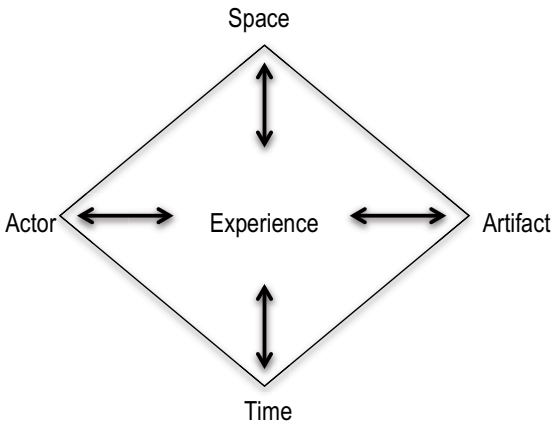


Figure 14. Specification of the schematic framework of experiential computing.

The initial experience is the lived experience where activities take place in the space (here), which occurs through time (process of now) and incorporates one actor (the user) and/or several actors (others) that interact with an artifact (the self-tracking device) or other artifacts (cars, trees, buildings) in the space. Simultaneously as the initial experience takes place, the technology (artifact; the

self-tracking device) captures the space, time, actor and artifact, which make it into an embodied relationship (ibid). The technology thus becomes a lens that exists between the initial experience and the user. It is able to mediate the initial experience. The mediation of the dimensions through the technology is thus a recall of the initial lived experience. The re-call presents the experience in a new visual format and instigates data engagement and data reflection, which may influence the perception of the experience.

The bi-directional arrows from the four dimensions indicate that technology, such as an artifact like a self-tracking device, frames the initial experience by being used by the user, but also that the mediated experience continues to influence the initial experience. For example, the space dimension is where the user performs intentional activities, such as running, and this is influenced by the presence of technology in the initial experience, but also when the user sees the data that is mediated. In this manner, the space frames the initial experience, the technology also frames the initial experience - and then the mediated experience frames the space dimension. The same applies for the other dimensions. The time dimensions points an arrow to the experience as it frames it through recording the duration of the experience. The arrow from the experience points back at the time dimension because the capture and mediation of the experience may influence the perception of time. Similarly, the actor dimension's arrow indicates that the actor(s) influences the experience because the user (or others in the space) participates in the spatiotemporal dimensions that are captured by the self-tracking device. The capture and mediation of the experience points the arrow backs at the actor dimension because the perception of self (or others) might also be altered. Finally, the artifact dimension arrow indicates that the artifact(s) also has an influence on the experience because the artifact(s) exists in the space where the user can interact with it. When the re-call is mediated through technology, the arrow also points back to the artifact dimension as the perception of the experience of the artifacts can be changed.

The conceptualization of the framework is now further elaborated according to the findings.

7.4.1 Space

First, space is a “structure that enables things to be connected as humans experience them” (Yoo 2010, p.219). The initial experience is embodied in the space because it is essential to have “physical, direct and existential participation” (Yoo 2010, p.218). This is as opposed to residing in a non-physical space, e.g. virtual reality space. The initial experience is thus lived in the space, as the user performs activities. While performing actions, such as walking or sleeping, the individual can only be in one place, namely the physical space. For example, the user can only do the regular morning jog through the park, but not while being in bed at the same time. While walking through the space, the self-tracking device captures the experience by gathering performance data, which is mediated as a visual expression through the number of steps and active minutes. The space is thus always present while performing self-tracking and the user cannot be rid of the space in both the initial and mediated experience. The mediated experience through the technology may influence the user to perceive the dimension in a different way.

The framework assumes that space frames the initial experience, but also suggests that the presence of experiential computing through capture and mediation of the experience influences the perception of the space. As mentioned earlier, the user can access the data at any time, as it is being collected and embodied simultaneously and successively through the technology. The exposure instigates the swift review-react-reflect-response process, which may bring new insights that alters the experience of the space. A satisfactory re-call of the data may then cause a transformation or distortion of the initial experience. In such an example, the user sees performance data that confirms or exceeds the perception of the initial experience, which transforms the understanding of the experience. The initial embodied experience is then transformed because of the mediation. Moreover, an unsatisfactory re-call may induce coping tactics that reject the technology’s embodiment of the data. For example, the user might initially consider the run as fast and successful in a beautiful green and luscious setting, but the data shows that it was slower than usual. This unsatisfactory data may cause the perception of the experience in space to transform or distort. In this case, the user might adopt a coping tactics, such as dismissal, that justifies the poor performance due to that the space was colder, windier or muddier than usual. The self-tracking device nor

activity then does not alter the space in its physical form, but the space is potentially perceived and experienced differently after the mediation.

7.4.2 Time

The time dimension explains that time is now, albeit “temporary and in the process of becoming” or “temporally emergent” (Yoo, 2010, p.219). Time is also experienced through the individual, i.e. the user. Time is a process that is always moving towards becoming, which makes it temporary and continuous. When it comes to self-tracking, time is a dimension that frames the perception of duration of the initial experience, but as time is being tracked, it can also be reported back to the user. In such a mediated experience, the time dimension places the personal data on a time line and in relation to the activities, such as sleeping and walking. The activities are thus evaluated in relation to the time data and may not be the same as the initial experience.

The framework assumes that time dimension frames the initial experience, but also that the capture and mediated experience of time may influence the perception of time. As the user is exposed to the personal data, the user might discover that the usual morning jog took much more time than usual. The initial experience of time is then influenced by the re-call of the experience through exposure of the data, and it changes the perception of the time of the activity. In many cases, the findings showed that the user would readily accept the time dimension as entirely true when it came to steps, yet would be more critical when it came to sleep. In such an example, the user would reject the sleep data by questioning whether the duration of sleep was accurate, as he or she had an intuitive feeling of when he or she went to sleep and the quality of sleep. The time dimension was more often questioned as an accurate embodiment due to the initial perception compared to the step performance. If the time data was the unsatisfactory, a coping tactic, such as procrastination, might be adopted where the user formulates an intention to improve the time dimension of the experience in the future, by attempting to shorten the time for the daily run or going to bed earlier. The time dimension might also impose dismissal, e.g. when it comes to sleep performance. In both examples, the technology plays a mediating role that influences the experience, which would not be possible if the user was not using it.

7.4.3 Actor

The actor dimension includes the user participating in the initial experience, but may also be the actors that reside in the spatiotemporal dimensions. This means that the actor may experience other actors while doing an activity. In a self-tracking context, the actor is engaging in an activity that is captured and then the exposure to personal data. The self-tracking activity means that the personal data is attributed to an individual user but this data may be influenced by other actors in the initial experience during the data collection.

The framework suggests that the actor(s) frame the initial experience, but also that the capture and mediation of the initial experience influences the perception of the actor(s). The user's continuous awareness and exposure to personal data leads to reflection on the dimensions and the self in terms of personal performance. For example, if the user performs poorly in relation to the goals, he or she gains awareness of it. In another example, a user found that the personal sleep performance was negatively influenced when he slept in the same bed as his girlfriend. The data is thus attributed to one user, but may be influenced by another actor in the space. In this example, the self-tracking user gained awareness that he had predominantly light sleep (as opposed to deep sleep) when his girlfriend spent the night. The user's initial perception of the experience was then influenced by the mediated experience and transforms the perception of the experience. In such a case, the user may accept the mediated experience alternatively reject it. The coping tactics that are used might then be intentional neglect where the user chooses not to look at the data when his girlfriend is visiting because it is likely to be unsatisfactory. Moreover, the influence of other actors may also come from the digitalization of actors, through the self-tracking app or other social networking sites (SNS), such as Facebook. In this case, the user must share the personal data with others through the app or on SNS. The social element has an influence on both the new and experienced users, where it often spurs social pressure and imposes normative social cues (Wogalter et al., 1989). The social elements, such as viewing others' data, indeed have a transformative effect on the user who proceeds to compare and compete with others (Froehlich, 2011; J. J. Lin et al., 2006; Ploderer et al., 2014).

7.4.4 Artifact

The artifact is something that exists in the physical space and can be digitalized through the use of experiential computing. In this research, the artifact can be the self-tracking device, but may also be the artifacts that exist in the space (such as trees, lamps, or buildings). When using experiential devices such as lifelogging cameras, the sensors can capture these artifacts, but this is not possible to the same extent with an activity tracker. When using an activity tracker, it is mainly the personal performance (such as steps and sleep) of the activity in the space that is embodied, rather than the artifacts surrounding the performance. Therefore, in this research, the artifact is primarily the self-tracking device that is interacting with the user to embody the experience.

The artifact plays a role as it influences the initial experience, and the mediated experience through the artifact may influence the perception of the artifact itself. An overall finding indicated that the mediated experience changed over time, depending on whether it was a new or experienced user. For example, the new user was more prone to experience the self-tracking device as a commitment device whereas the experienced user were less conscious of its existence. The experienced users perceived it more as an information tool that works at convenience. Thus, the initial experience is influenced by the mediated experience and transforms the perception of the artifact as well as the experience. For example, in the beginning, new users conformed their behavior to reach the goals. However, several new users argued to have eventually changed their view on the self-tracking device after having seen personal data that did not correspond with the initial intuitive experience. One user expressed that he was convinced to have walked more steps than was illustrated in the data dashboard. This caused a rejection of the data as the artifact was considered less reliable. The experienced users encountered the same scenario, but said that they chose to trust it due to that it was consistent, albeit temporary glitches. In both cases, dismissal was exercised of the mediated experience. The interaction between the artifact and the user transforms the experience, but also transforms the relationship to the artifact itself. The influence of the artifact on the experience was greater in the beginning, compared to deterioration over time.

7.4.5 Summarizing the framework

The aim of specifying the framework is to be able to further discuss the perception and experiences of personal performance that is mediated through self-tracking devices. As proposed, the four dimensions are vital in framing the initial experience but they are also influenced by the mediation of the experience that occurs through the chosen technology, such as a self-tracking device. The bi-directional arrows are incorporated in the framework to illustrate and assume the influence of the presence of experiential computing has on the experience. The initial experience is then not static within four dimensions, but changes with the inclusion of experiential computing.

The findings also shows that an experience can be transformed both when the user accepts and rejects the mediated experience, which may then both facilitate and constrain the experience. In other words, the initial experience can be constrained by the data available while it also facilitates a new possible perception of the experience. Based on the findings, the rejection response to the mediated experience has a predominant role in the discussion. The rejection response often means that the user attempts to find a neutral state, due to having a status quo bias. Therefore, the user creates a new experience in which this is possible, such as using coping tactics. The coping tactics help the user create a new experience where the data can be accepted, such as dismissing the data, procrastinating by achieving acceptance later, only looking at numbers to accept and neglecting until data is acceptable. The user adopts the coping tactics to be able to accept the data, even though they are rejecting some of it in the process.

7.5 Implications for practice

The research contributes to practice by introducing a greater understanding of the new as well as the experienced self-tracking user, the engagement and the complexity of perceptions related to the use of experiential computing. The research acknowledges the user's struggle with the dual self in engaging and reflecting on personal data, which leads to further complexities in the aspiration to design tools that adequately support both new and experienced users.

The increasing dispersion of self-tracking mobile apps and wearable devices suggests that there is a stronger demand to understand the user who adopts these.

However, the current literature related to experiential computing places a primary emphasis on the technology's capabilities and the design so that it can capture the performance measures of the individual user. This is as opposed to taking the perspective of the actual user experience and the path that takes place. In order to refine and improve design, the findings of this study shows that the focus should shift to consider the similarities and differences between new and experienced users. This dissertation has researched self-tracking activities from the user's perspective and proposes that the results are useful when developing and designing for both new and experienced users. Therefore, the suggestion is to focus on the user experience process rather than the capabilities of the self-tracking device as a digital measurement tool. This is because while each user is new, self-tracking is continuous, and the user changes awareness, goals and motivation along the way. In fact, the user is accumulating personal data for a digital archive that can potentially run for several years, which suggests that the lifecycle should be considered in both short term and long term. For example, the notifications or reminders incorporated into the systems seemingly have a strong effect on users to stay motivated to maintain a behavior, and where the device becomes a commitment device. On the other hand, the experienced users tend to ignore the notifications as they argue they already are aware of their patterns. Nevertheless, the ignoring of notifications might be due to the exercising of coping tactics, as a way to circumvent sense of failure. Therefore, the design must consider how to integrate measures that cater to this response, but also those that circumvent it. By considering the lifecycle in a more extensive way, there is a possibility that the user continues to use the self-tracking tool for an extensive time.

The rejection of personal data is central to the findings and underline the emergence of users adopting coping tactics to deal with unsatisfactory data. The theoretical background underlined the importance of engagement with the personal data for the user to continue using and performing according to the set goals. However, the findings highlight the possibility that one of the reasons for this lack of engagement is due to the fact that the user rejects the data because of unsatisfactory data, causing coping tactics to arise. The coping tactics indicate a change in behavior that cannot be traced by merely tracing the use of the app or the performance measures. Instead, the coping tactics shed light on how users deal with unsatisfactory data by averting from the intended and designed experience.

The findings thus showed that performance and perceptions on performance are not always rationally related. The recommendation to practitioners is to consider how these coping tactics can be addressed in the design of device and mobile apps to help user cope with personal data, and so that it does not lead to discontinuance.

The use of self-tracking devices are already being noticed in the field of sports (Williamson, 2014), medicine (Prince, 2014) and education (V. R. Lee, 2013), however, there is also an emerging interest from the textile industry. As self-tracking devices are often worn as individual pieces of technology (i.e. wearable technology), there are also great possibilities to extend this into items of clothing for both leisure and sports. The wearable tech business is predominantly dominated by sporty and male centered, but should consider including a more female demographic in the design aspirations. For example, collaborations between Fitbit and Tory Burch as well as Intel and Opening Ceremony are tickling the interest of a wide audience. As such development increasingly transpires, the self-tracking possibilities are even more seamlessly integrated into the daily life.

7.6 Future research

There are several ways to continue the research field presented in this dissertation. A few of suggestions are presented in this section, yet the scope surely reaches beyond these.

The possibilities for self-tracking for private use is increasing with the growing availability of wearables and mobile apps on the market. The research should be conducted in alternative contexts and involving a variety of the various available devices on the market. The positioning of another context for self-tracking might inspire different perceptions and instigate different performance pattern among the users. As noted in the theoretical background chapter, a challenge exists in the abundance and insufficiency of data exposed to the user and therefore, the technological development that caters to this would be interesting to follow. For example, the app Azumio uses the smartphone's camera to collect pulses of the heart rate. By placing the finger on the camera, light signals are sent out and then the color changes are tracked in the light that passes through the finger, which is a technique also used by medical pulse oximeters. Moreover, many of the major

brands, such as Jawbone UP and Fitbit, have incorporated heart rate monitors in their latest devices. Thus there are self-tracking areas that are increasingly focusing beyond merely steps and sleep in terms of tracking well-being. These developments allow additional kinds of personal performance data on various aspects of everyday life to be easily gathered and monitored. In turn, it is an opportunity to explore perceptions and performance in relation to supplementing contextual data for the user. The performance, as in behavioral changes, might be altered when the user is exposed to richer data sets. For example, people with medical conditions, such as diabetes, might be able to compare and contrast information against their daily measurement of insulin levels.

The context of organizational tracking is also intriguing. This dissertation focused primarily on the user as a private individual in an everyday context, where the gathered data was mainly accessed for private interest. The aspirations, goals and perceptions about performance are likely to be highly individualized and anchored in the personal social context. However, an organizational context invites the user to engage with personal data by adding a layer that extends beyond the personal interest, and imposes rules, regulations and other social norms. Indeed, the concept of measurement is by no means a novel activity in the organizational sphere, and the implications for tracking various personal aspects of the user, such as time spent on tasks, meetings, and even personal health, summons questions of both a structural, functional and ethical nature.

Longer field studies are relevant to understand the changes in both perception and performance that occur from a new user to an experienced user and onwards. The field study conducted in this project was under the duration of a minimum of 21 days with 34 users. The field studies were time-consuming and challenging to conduct, especially due to the difficulties and glitches arising from the devices breaking and not syncing, among other issues. However, as technology becomes more advanced and readily available to the public, the self-tracking studies could be designed to be made more encompassing in terms of user needs and systems, but also more affordable and potentially more accurate. The current study provides a great departure point in understanding the initial time with a self-tracking device, but an extended study would give it more statistical rigor on user perceptions and performance over time. In relation to this, it would also be interesting to study the users who have discontinued their use and how this process emerges.

Finally, the issues of privacy and transparency of the self-tracking data is another relevant discussion on the rise. The increased use of experiential computing devices that have sensors and gather information about the user's daily routines and long-term habits creates a massive archive of data. In the context of discussing such a large amount of data, the use and dispersion of such data is relevant for governments, organizations and the user alike. For the purposes of this dissertation's research question, it was a conscious choice not to include a lengthy discussion on privacy and transparency of personal data, as this could be considered a topic for a dissertation in itself.

7.7 Concluding remarks

The emergence of experiential computing is highlighting an increasingly intimate relationship between the individual and technology as it is establishing a stronger presence in our every day lives. Alongside this intimacy, the relationship is also gaining increasing complexity in how we interact, react and respond to the co-existence. This research is fuelled by the interest to investigating the complexity that arises through the dispersion of experiential computing with a focus on self-tracking activity.

Two empirical studies on new and experienced users were conducted to further investigate the experiences in the everyday relationship between technology and the individual. Earlier studies primarily focus on the technology's capabilities, but this research focuses on the individual's capabilities and cognitive processes in relation to processing the exposure to personal data. A central finding suggests that the user's lived experience is carefully by albeit continuously influenced by the engagement with the personal data sustained from self-tracking. The engagement with the data leads to a reflection process that then potentially transforms or even distorts the initial experience. Therefore, the mere presence of the technology to capture and mediate data on personal performance influences the user in all stages (pre, during and post) of the lived experience. However, the user does not necessarily adopt a strategic or calculated approach to analyze the personal data, but rather undertakes an awareness of self. The awareness is initially strong but grows inherent and subtle over time.

At the same time, the user also exhibits rejection of the awareness, which follows by adopting coping tactics to deal with the tremor. These coping tactics are ways for the self-tracking user to deal with unsatisfactory data and emerges due to the existence of a dual self. The dual self's systems aid both the new and experienced users in the reflective process.

This research on the development of experiential computing in everyday experiences has brought forward an intriguing account of the presence of technology and user interactions. As the intimate relationship develops and disperses across one or several different technologies with additional and advanced functionalities for facilitating self-tracking, there are exciting possibilities for how the user-technology companionship might evolve. I hope to take part of this correspondence, both by capacity of a personal and professional passion.

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10. APPENDIX

The search for literature

The search for relevant literature was primarily done by using a specific set of keywords in search engines followed by going over titles and eventually, abstract. This section presents which keywords were used and how the relevant sources were identified among the search results.

Firstly, the departing search term in the literature search was “experiential computing”. The search lead to a small yet select sample of highly relevant articles that present the definition and discuss the nuances of the concept. Two key articles are established as Yoo (2010) and Jain (2003) due to content and dispersion in the IS field. Thereafter, the articles’ bibliography and citations were reviewed to both backtrack and identify future references. The backtracking of references is useful to understand the author’s framing of the article while the future references are valuable to understand how the discussion has evolved since then. This procedure enabled the literature search to expand the article pool by looking at historical references and future references.

Secondly, the focus on an area within experiential computing lead to using the terms “self-tracking” and “Quantified Self”. The activity of self-tracking is a central term that denotes the main interest, whereas the secondary term “Quantified Self” represents the community in which self-tracking occurs. The “Quantified Self” is recognized and often used both in academia and industry when discussing self-tracking. The subsequent search produced great variety of articles related to the phenomenon. In this search, several other terms emerged, such as “personal informatics” and “lifelogging”. However, these are categorized as sub-streams under the term self-tracking and are thus not considered as primary search terms but rather as an indication of relevance of the article. The terms were used to identify key articles where the backtracking and future references were reviewed for understanding the discussion.

The search terms were all used individually with quotations marks (i.e. “self-tracking”) in the respective searches to make the search as narrow as possible. The

searches were made with the terms individually. The below table presents the results.

	Ebscohost journal articles	Ebscohost conference proceedings	Google scholar results (since 2010)	Titles and abstracts scanned	Final article pool
Experiential computing	6	0	486	104	5
Quantified Self	20	4	1753	923	20
Self-tracking	19	1	1607	701	68
Total	44	16	4024	1832	95

Table 22. Search results through Ebscohost respectively Google Scholar.

The search for relevant literature was made by using Ebscohost and Google scholar as well as the related platform Web of Science. The Ebscohost database generated a small sample of results, of which most were journal articles. The term “Quantified Self” produced the most search results in terms of both journal and conference articles. The search on “self-tracking” produced several journal articles as well, and one conference proceeding. All the articles were found relevant. However, due to the limited results found in the Ebscohost database, another search investigation was done through the Google Scholar database. The searches on the different databases generated a great deal of overlapping articles; all Ebscohost results were found on Google Scholar. Further, the Google Search results showcased a greater amount of search hits that was not available in the earlier search. Google scholar might therefore be useful to get a larger overview into both scholarly and non-scholarly material. However, the Google Scholar search results do not filter according to source type (i.e. journal or conference proceedings), which means that it is more difficult to filter out unreliable sources (Falagas, Pitsouni, Malietzis, & Pappas, 2008). Google scholar is useful to get an overview, yet many search results are not peer-reviewed outlets but self-published texts which causes the above issue (Jacsó, 2005). On the other hand, the Google scholar results are attached to the platform Web of Science, which is a scientific

citation indexing service. The platform allows the user to search on topics much like in Ebscohost and Google scholar, yet has additional features such as viewing citations by others, creating citation reports and citation maps. This tool allowed a more transparent overview of how a topic has emerged as well as evolved over time.

Nevertheless, the Google Scholar search presented itself with some restrictions that caused additional work for the researcher. More specifically, it is not possible to narrow the Google Scholar search results so that it only scans words in the abstracts. Therefore, the search results' abstract must be manually reviewed. Indeed, each search result was first scanned by the title and if the title were relevant to the other search terms then the abstract would be scanned as well. If both the title and the abstract were relevant, then the article was selected as a part of the reading list. This process was conducted to identify the most relevant articles. A vast majority of the abstracts were discarded, as they were not related to the research interest. Instead, many search results related to self-tracking were loosely applied to other research areas, such as biology and physics. Other articles were discarded because they were self-published, opinion pieces, not peer-reviewed and therefore not scientifically rigorous enough to be included.

The final article pool consists of 93 relevant articles to discuss the research context and grant a further understanding of the research interest. According to this article base, the most search results comes from Quantified Self, followed by self-tracking and then lastly, experiential computing. The concept of Quantified Self, as well as self-tracking, has developed mainly since around 2010, where it started to gain traction. The chart below illustrates this development across the three search terms. These results indicate that experiential computing is niched and exist mainly an IS context, whereas the Quantified Self and self-tracking are terms that are adopted more widely and across several scientific fields.

After an article pool had been established, the review of the literature was conducted by importing the articles in the coding software, MaxQDA, in which the articles were individually read, coded and analyzed. The key features of the literature were identified by reading, which was then followed by summarizing commonalities. Then these commonalities were merged into larger conceptual groups. To add nuances in the conceptual groups, sub-coding also occurred. For

example, some categories are behavior, reflection, and application. These are general categories used while coding the interviews. After the articles had been read and categorized according to the general categories, a sub-coding occurred. This meant that the category “reflection” got sub-groups such as memories and non-reflection. The coding is useful in gaining an overall view of the literature and identifying common themes as well as sub-themes.

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